BANKRUPTCY STUDIES: EMPIRICAL WORKS ON PREDICTION AND FINANCIAL MARKETS

By

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Finally, I want to dedicate my dissertation to a new future for my homeland, China. The lessons and memories of May and June 1989 will be remembered forever.

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This dissertation studied two areas not covered by current bankruptcy research. First, the question whether financial markets could assess bankruptcy risk beforehand was addressed. Second, the problems of long-term bankruptcy prediction models were discussed, and a new model with reasonably accurate long- as well as short-term predictive powers was developed.

On the subject of financial markets, this dissertation looked at whether the market could assess bankruptcy risk ahead of time. The risk premia of corporate bonds of bankrupt companies were used to investigate whether there was any rise in risk premia as companies approached bankruptcy. Then, an event study was done to determine whether bond downgrades affected the performance of a later-bankrupt company's stock's daily rates of return.

It was found that risk premia did increase as companies approached bankruptcy, and that the risk premia of companies which were later liquidated rose more than the risk premia of companies which later re-organized. The event-study showed that the daily rates of returns of stocks of companies which later went bankrupt did fall significantly during the first downgrade, unlike those of companies which did not.

On the subject of bankruptcy prediction, this dissertation looked at whether an accurate, long-term bankruptcy model could be developed using variables which assess a company's fundamental characteristics as well as its current financial position. A model based on the following eight variables was developed: return on assets, fixed charge coverage, balance ratio, market-to-book ratio, relatedness ratio, net rate of management stock acquisitions, relative sales growth, and capital intensity. It had achieved high classification success and predictive accuracy, and, unlike those of past models, its predictive powers did not decrease over time.

Finally, work was done on the use of logist analysis in bankruptcy predictions. It was shown that any non-random, state-based sample selection technique would distort the probabilities generated by logist models. A formula was derived to remedy this problem by providing an adjustment scheme whereby the resulting probabilities could be made to work for a general population.

CHAPTER 1
OVERVIEW AND OUTLINE

Topic Overview

Bankruptcy is one of the most important topics in modern finance. It plays a strong, visible role in all dimensions of financial economics, such as the efficient market theory, portfolio theory, capital asset pricing theory, option pricing theory, and agency theory. Thus, understanding bankruptcy is important to financial research in both theory and practice. In theory, if we thoroughly understood the dynamics and causes of bankruptcy, we should be able to make the risk of bankruptcy a parameter in market valuations of debt and equity. Assuming that investors are naturally risk averse, such formulas can determine how the probability of bankruptcy affects the average investor's utility. In practice, researchers have tried to develop predictive models of bankruptcy that can alert interested parties to the impending dangers of bankruptcy before it is too late to take corrective actions. Because practically any group involved with a company would be interested in the risk of bankruptcy it

faces, potentially widespread demand for such a model has inspired much research in this area. To date, several approaches have been taken to develop predictive models; they are discussed in the Literature Review section.

While substantial work has been done on various aspects of bankruptcy, including empirical forecasting and prediction, we believe that past works have left a few areas unexplored. First, many successful predictive models of bankruptcy have been developed, but most of these models base their assessment of a company's bankruptcy risk primarily on its current financial position. They rely heavily on such accounting data as retained earnings and capitalization ratios. Some of these predictive models have grown quite complex. Because they use mostly current financial data, however, their predictive power is limited to a relatively short period before bankruptcy, usually one year. When they are used to predict bankruptcy further into the future than one year, their accuracy falls significantly.

Second, no one, to date, has studied whether the market can somehow predict bankruptcy. Modern finance considers financial markets to be efficient, but no research has yet been done on whether this efficiency extends to the evaluation of companies' bankruptcy risk. After all, if the market were truly efficient, then it should include the risk of bankruptcy as one of the determinants of the value of a company's securities. Hence, the market's assessment of a company's

securities' risk should include as a component the company's chances of bankruptcy.

In this dissertation, we address both of these areas that present bankruptcy research has largely overlooked. First, we explore the market's ability to "sense" coming bankruptcy by looking at the risk premia of corporate bonds. We first examine whether such risk premia rise as the event of bankruptcy approaches. Then, we investigate what role the bond rating agencies, Standard & Poor's and Moody's, play in the market assessment of a company's overall risk in general and bankruptcy risk in particular. In other words, if the market actually does include bankruptcy risk in its overall assessment of a company's risk, then how do S&P's and Moody's ratings affect this market assessment? Do they provide new information to the market and, therefore, serve as a crucial link in the process, or does the market itself already reflect all of the information these rating agencies provide?

To answer this question we have to study two problems. First, assuming that the first consistent downgrade of a corporate bond provides the most relevant information, we determine whether S&P's and Moody's downgrades precede or follow increases in the bond's risk premium.[1] Second, with the same assumption, we explore what impact, if any, the first bond downgrade has on the performance of the company's stock. Arguably, if nothing happens to the stock's return or the bond risk premium after a bond downgrade, then we can infer that

the market has already absorbed all the information S&P's and Moody's provide in the rating change. In that case, we can say that S&P's and Moody's provided no new information in the market's assessment of a company's bankruptcy risk. If, however, the market reacts strongly after a bond downgrade and the bond's risk premium rises or the stock return changes significantly with the downgrade, then we can say that S&P's and Moody's do provide new information to the market in its assessment of bankruptcy risk. In that case, we can further conclude that bond downgrades are good indicators of increased bankruptcy risk and correspondingly higher risk premia.

To study bond risk premia and bankruptcy, we first compile the yield-to-maturity of bonds of companies that went bankrupt and subtract from them the yield to maturity of government bonds. Then, to assess the impact of bond rating downgrades, we use the methodology known as "event study," which is described in greater detail later in Chapter 3.

The second area that has largely been overlooked in bankruptcy research is the "nearsightedness" problem of current predictive models of bankruptcy. We attempt to overcome this shortcoming by building an empirical model that includes new sets of variables with a long-term orientation. We believe that as one tries to predict bankruptcy farther ahead in time, a company's current financial position becomes less significant, while other, currently unexplored factors play increasingly larger roles. For example, a company's

current return on assets (ROA) may be critical to whether it is solvent or bankrupt within the next few years, but its long-term financial health would probably depend less on current profit levels than on the fundamental characteristics of the company that predetermine future ROA. Hence, to make accurate long-term bankruptcy forecasts, we must examine not only a company's current financial position, but also its more fundamental operating characteristics, such as its lines of business, degree of diversification, management efficiency, and growth.

We adopt this approach to develop an empirical model of bankruptcy that can forecast the extent of bankruptcy risk. In addition to a group of four variables designed to assess a company's current financial position, we adopt variables that describe a company's management ownership position, its degree of diversification, the lines of business in which it operates and their relationship, and its growth relative to the rest of the industry. We expect that a model based on this broader specification of variables will have high long-term as well as short-term predictive powers.

Dissertation Outline

In the following chapters, we present the research design and findings of our dissertation. Chapter 2 examines current literature on both bankruptcy prediction and the effects of bond rating changes, which, as stated earlier, are used to

study financial markets' signals about bankruptcy. Chapter 3 discusses the techniques and methodologies we employ to study the financial market's ability to sense impending bankruptcy. Then Chapter 4 identifies the data sources for our work on financial markets and bankruptcy and presents the results we obtained in the market-oriented part of the dissertation. Chapter 5 discusses in depth the rationale for and the variables used in our empirical model of bankruptcy. Attention is focused on why each variable was chosen, what values each variable should have, and what we expect our model to tell us about the role each of our variables should play in assessing bankruptcy risk. In Chapter 6 the methodology we used to build our empirical model is described. This is logist analysis, and we will discuss the advantages it has over the more traditional discriminant analysis. Chapter 7 gives the results we obtained from tests of our empirical model. Finally, Chapter 8 summarizes our research, presents the conclusions we reach, and points out possibilities for future research.

Note

1. "Consistent" means a bond downgrade after which there were no upgrades until the company filed for Chapter 11. In other words, this downgrade is the first of a series of downgrades which eventually lead to bankruptcy, uninterrupted by any upgrades of the same bond.

CHAPTER 2
LITERATURE REVIEW

Summary of Current Literature

Market Efficiency Studies of Bond Rating Changes

Katz (1974), in one of the earliest works on bond rating changes, developed an event-oriented methodology for testing the efficiency of the bond market. He looked for "unusual behavior" in a bond's yield to maturity twelve months prior to and five months after a rating change. His data consisted of electric utilities bonds from 1966 to 1972. Katz derived a quadratic regression equation of yield to maturity at any given time, t, based on maturity, total float, and coupon rate. Then, he compared his expected yields with the actual yields and the changes in the actual yields with premium differentials of two rating classes. He concluded that no anticipation exists prior to a public announcement of a rating change. After the rating change, there was a lag of six to ten weeks before yield-to-maturity fully adjusted to the new rating class.

Weinstein (1977) tried to determine if bond rating changes contained new information by studying the bonds' prices during the time period surrounding rating change announcements. His sample consisted of utilities and industrial bonds from July 1962 to July 1974. Weinstein started with portfolios which, for every month, contained all bonds with a given rating. He then constructed a series of risk-adjusted returns for each bond by subtracting the return on the appropriate rating class portfolio from the return on the given bond. He selected the bonds that had a rating change and looked at if those bonds had abnormal returns during periods of rating changes. Weinstein concluded that bond rating changes caused no significant price change during or after the announcement, and that adjustments in the market were made 18 to six months before the event. Hence, his study suggested that rating changes provided no new information.

Pinches and Singleton (1978) studied the effects of bond rating changes on the market returns of stocks during the period from January 1950 to September 1972. For each stock, they derived a market return based on its beta and measured the actual return against the expected return for a period of thirty months before to twelve months after a rating change. Their study calculated disturbance terms (residuals) of stock returns during the period. Pinches and Singleton concluded that all changes attributable to companies' financial situations were fully anticipated 15 to 18 months ahead of

time, while all changes attributable to company-specific events were anticipated six months ahead of time. Thus, although there were abnormally high and low returns corresponding to upgrades and downgrades, respectively, before a rating change, there were normal returns after the rating change. Again, a study concluded that bond rating downgrades provided no new information to the market.

Finally, Griffin and Sanvincente (1982) used three different methodologies to study the effects of rating changes on common stock prices. Their study contained 180 rating changes from 1960 to 1975. First, they used a portfolio method similar to that of Weinstein (1977). Then they employed a one-factor and a two-factor model, basing their expected stock prices on betas, as had Pinches and Singleton (1978). They found that although rating upgrades had no effect on stock prices, downgrades did have significant effects. Because of the inconclusive nature of their results, further research in this area was necessary.

The methodology employed in this dissertation differs from previous works in several important ways. First, previous authors used yield-to-maturity, an absolute value, as their indicator of return. It is our position that absolute yield-to-maturity, in this application, is not an accurate measure of return. Instead, we suggest using a relative value, the risk premium, which is defined as the difference between a bond's yield-to-maturity and the yield-

to-maturity of a risk-free security. Second, we construct our samples not by industry but by the nature of the event. In other words, we defined the event as the filing of Chapter 11 under the Federal Bankruptcy Act. As far as we know, this is the first study of bond rating changes to be based on data of companies from all industries.

Theoretical Models of Bankruptcy

Wilcox (1971) is one of the earliest and most primitive theoretical models of bankruptcy. It assumes that a company starts with a positive amount of capital, K, which changes randomly over time. Positive changes in K indicate positive cash flow and increases in the company's assets, while negative changes in K indicate financial losses which require the company to liquidate assets. When a company's K is sufficiently negative, it becomes bankrupt. Expressions for the expected probability of bankruptcy, as well as time to bankruptcy, are mathematically derived, just as they would be for the gamblers' game.

Scott (1976) and (1977) attempted to improve on this simple model. Scott's early models assumed that a company has a potentially infinite life and can meet losses by selling debt or equity in an efficient market without incurring flotation costs. They further assumed that the secondary market for real assets is imperfect and that a firm begins

with an optimal level of assets. Therefore, it would much rather sell securities and debt than liquidate assets to cover its losses. Scott then showed that a company would remain solvent as long as stockholder wealth, measured by market value, remained positive.

Scott (1981) developed a revised version of the earlier model. In this newer model, Scott assumed that a company may have imperfect access to external capital, so it might incur flotation costs when it sells securities, or there may be a tax system which favors internally-financed corporate investments. Further, systematic imperfections in the market valuation of securities can hinder corporate access to external capital. This model, however, also assumed that the company has no debt and can issue only equity. Thus, according to this model, a company will go bankrupt when the market value of its securities is less than the amount of investment needed at times of negative income. Therefore, bankruptcy is not the result of a conflict of the benefits and costs of debt, but rather the product of investment managers' mistakes.

Empirical Works on Bankruptcy

Beaver's 1966 paper was the first empirical work that tried to build a predictive model of bankruptcy. He looked at 30 accounting ratios which could be used to predict

bankruptcy, and for each ratio he derived a cut-off point for bankruptcy. He concluded that three ratios were the best predictors of financial failure: Cash Flow/Total Assets, Net Income/Total Debt, and Cash Flow/Total Debt.

Altman, Haldeman, and Narayanan (1977), a follow-up of Altman (1969), used the more complex multi-variate discriminant analysis approach to build a predictive model. Their work included all industrial failures from 1969 to 1975 with at least $20 million in assets, which made a sample of 53 bankrupt firms, and Altman et al. found a matching sample of 58 non-bankrupt firms. The samples were matched by industry, year of bankruptcy, and size of assets. Their model included seven variables: return on assets (ROA), stability of earnings, debt service (times-interest-earned or TIE), cumulative profitability, current assets/liabilities ratio, capitalization, and size. After using various statistical techniques, Altman et al. derived a value ZETA as the cut-off for bankruptcy. This model, commonly known as the ZETA model, is highly accurate, especially when bankruptcies are near. Today, it is the leading model for predicting bankruptcy, and because many financial institutions use it, it has become an industry standard.

Ohlson (1980) took another approach to bankruptcy prediction by using logist analysis to build his model. His sample included 105 failed firms, but he did not find a matching sample by asset size. Hence, among his nine

variables, size became the most significant one. Since his model had error rates of 17.4% for non-bankrupt (type I error) and 12.4% for bankrupt firms (type II error) even just one year before bankruptcy, it has remained more-or-less an academic curiosity and has not attained the same widespread use as Altman's ZETA model.

Zavgren (1985) extended Ohlson's work by including more variables and extending the length of the study. Her work looked for the important factors in the short- and long-term predictions of bankruptcy. Zavgren found that profitability was not significant in either the short- or long-run. Rather, her study showed that the ability to meet obligations is significant in the short-run, while efficiency ratios and liquidity are important in the long-run. Zavgren's study, then, reduces a company's bankruptcy risk to two issues, that of short-term endurance (as measured by the ability to meet obligations) and fundamental characteristics (as measured by the efficiency ratio and basic liquidity.)

Significance of this Dissertation

While the existing literature is already quite advanced, we believe a few areas have been left unexamined. First, while work has been done on bond rating changes, there has been no research that tries to link bankruptcy with financial market reactions. No one to date has looked at the trend that

bond risk premia take as a company approaches bankruptcy, even though bankruptcy risk, in theory, should be a primary risk included in risk premia. Further, while researchers have studied bond rating changes' effects on both the stock and bond markets to see if such rating changes contained new information, no study has linked the information these downgrades provide with a company's risk of filing for Chapter 11 and thus declaring bankruptcy. Since bond downgrades are meant to warn investors of possible default and bankruptcy, whether such downgrades have any impact on financial markets should be directly linked to the market's assessment of a company's bankruptcy risk. So far, however, research has left this area untouched.

Second, as we stated in the previous Chapter, current bankruptcy prediction models have looked mostly at current financial data. Only Zavgren (1985) has tried to examine certain fundamental characteristics, and her study shows that such information does indeed have a role in empirical studies of bankruptcy, especially when we are dealing with long-term bankruptcy prediction. Hence, we assert that fundamental characteristics have largely been overlooked by present bankruptcy research, and our dissertation will address this area more systematically than Zavgren did.

Our research contributes to the financial research of bankruptcy and market efficiency in several ways. By studying the bond market and bankruptcy, we attempt to determine

whether the financial market can adequately assess bankruptcy risk on its own and whether bond ratings play a part in this assessment of risk. We then look at ways to augment or reinforce market signals via prediction models with significant early warning capabilities. In this regard, our study covers a period longer than those of its predecessors. Further, we introduce variables that assess the fundamental characteristics of a company to forecast long-term bankruptcy. On the theoretical side, this research can lead to establishing a relationship between certain fundamental characteristics of a company and its financial position a few years into the future.

In the area of market efficiency, we attempt to assess whether the markets are truly efficient in anticipating one specific type of risk--bankruptcy risk. Further, in our event study, we study whether the bond rating downgrades actually do provide new information to the market. We do not, however, do this by merely looking at whether the downgrade trailed or led a rise in the risk premium, because we believe such indications are in themselves not significant. After all, a downgrade that trails a rise in risk premium might be regarded as the leading downgrade to a subsequent rise in the risk premium. Hence, we will instead concentrate on whether downgrades make a significant impact on the market.

CHAPTER 3
METHODOLOGY TO STUDY FINANCIAL MARKETS AND BANKRUPTCY

Our research on financial markets and bankruptcy encompasses two topics. First, we look at the trend of the risk premia of corporate bonds of companies that later went bankrupt. This trend tells us if the markets can correctly assess increasing chances of bankruptcy and default as bankruptcy nears. Then we examine the impact of bond downgrades on the returns of a company's stock. We determine if ratings play a significant role in providing the market with new information.

To study whether bond risk premia increase as a company approaches bankruptcy, we selected a sample of bonds based on two criteria. First, they had to be publicly traded bonds listed in the Standard & Poor's Bond Guide with a bond rating from either S&P's or Moody's. The second criterion was that the companies which issued the bonds later filed for Chapter 11 between September 1977 and October 1988. Only 50 corporate bonds had bond ratings and other available data from S&P's or Moody's adequate for our purposes. These 50 bonds, listed in Table 1, are used to study risk premia and bankruptcy. Then,

from the Analytical Record of Bond Yields and Yield Spreads, published by the Salomon Brothers, we obtained the monthly yield-to-maturities for US government securities. The risk premium for each of our companies is the excess of the yield-to-maturity of its bond over the yield-to-maturity of an US government bond with the same maturity.

We then studied the risk premia of our 50 companies as they moved towards bankruptcy. We separated the companies into two groups--those companies which later re-organized and those that were later liquidated.[1] Next, we compared the risk premia of bonds in those two groups as the companies approached bankruptcy to see if the market's assessment of risk went so far as to differentiate companies which could later re-organize from those that could not.

To study the impact of bond downgrades, we use the event study methodology. An event study compares the impact of an event on security holders with the predictions made by a model that approximates what would have happened if the event had not taken place. In effect, we try to compare what happened with what a model tells us should have happened. Our event is the first consistent downgrade rating change, and the size of the impact is measured by the disturbance of the stock's daily rates of return. The number of months between the first downgrade bond rating change and the month of filing Chapter 11 for our sample is given in Table 2.

In our work, the Mean Adjusted Returns Model, as

discussed in Fama (1976) and Masulis (1980) is used as the basis for the statistical studies. This model uses the mean returns on an individual stock over a representative period of time before the event period to estimate a stock's expected mean return. This "comparison period" is then compared with the daily rates of return over the period of rating change.

Because our research focuses on financial distress and bankruptcy, both of which are long-term processes, we selected a two-year time period before the event as the "comparison period." Since there are a different number of business days in any given year, we simplified things by defining 510 business days as "two years." Thus, our comparison period is 510 days to 11 days before the rating change. The actual event, the bond rating change, is taken as the 21-day period beginning ten days before and ending ten days after the downgrade announcement.

For this study, we construct a sample of companies that were listed on the New York or American Stock Exchanges, that had bond downgrades, and that later filed for bankruptcy. We then found a matching sample of companies that satisfied the first two criteria but did not later file for bankruptcy.

Once we have used our comparison period to determine a stock j's mean daily return, μ_j, the event period disturbance term E_{jt}, which measures the impact caused by the bond rating change, is given by:

$$E_{jt} = R_{jt} - \mu_j,$$

with t being the date in the comparison period, $t = -10..10$,
where R_{jt} is the realized daily return of the stock j at time t, which was read from the CRSP Daily Return Tape.

The average disturbance term for N events (firms) is:

$$\text{avg } E_t = 1/N * (\Sigma E_{jt})$$

with $j = 1..N$.

The null hypothesis, avg E_t equals zero, means that a downward bond rating change has no effect on shareholders' daily returns. Since we believe that the first downgrade of a bond gives the earliest signal and, hence, the most information to stockholders about the risks of financial distress, we expect the null hypothesis to be rejected for our Chapter 11 sample. Conversely, we expect not to be able to reject the above null hypothesis for our matching sample of firms that did not file for Chapter 11.

The variance of avg E_t is:

$$\text{Var (E)} = (1/499) * \Sigma (\text{avg } E_t - X(E))^2$$

where $X(E) = (1/500) * \Sigma (\text{avg } E_t)$

When t=0, we would be testing for the disturbance on event date. The t-statistic used to determine whether avg E_0 differs significantly from zero with 499 degree of freedom is:

$$t = \text{avg } E_0 / \sqrt{\ } (\text{Var (E)})$$

The cumulative error over a particular event time interval is:

$$CE(a,b) = \Sigma (\text{avg } E_t)$$

where $-10 \le a < b \le +10$

We hypothesize that the cumulative errors in the bankrupt and matching groups are statistically different, implying different effects of bond rating changes on stock rates of return.

Finally, we separate the Chapter 11 group into two sub-groups: one sub-group of companies that filed for Chapter 11 and later re-organized and another of companies that filed but were later liquidated. We compute an average E_t for bond downgrades of companies in the two sub-groups. Then, we employ the t-test and F-test to analyze the differences for statistical significance between the two sub-groups. The null hypothesis is that the means for the two sub-groups of companies should become statistically equivalent. By reasoning explained previously, we expect that the null hypothesis will be rejected. Thus, we expect the means for the two sub-groups of companies to become statistically significantly different as we approach the filing of Chapter 11.

Note

1. A company, by our definition, is "liquidated" if it satisfies one or more of these conditions:

1. acquired by another company or liquidated
2. listed on COMPUSTAT as "bankrupt"
3. no longer on the Wall Street Journal Index
4. no longer on the Predicasts F&S Index of Corporate Change
5. no longer on Q-file
6. no longer on the Directory of Corporate Affiliations
7. no longer listed on the C-D System
8. no longer described in the Chapter 11 Report

Table 1. Bond Sample for Risk Premia Studies

Company Name	Bond Name	Ch. 11	Ind.
Allegheny Int'l	Sub SF Deb 10.40% '2002	8802	17a
Allis-Chalmers (Mfg) Corp	SF Deb 4.85% '90	8706	41
Amarex Inc	Sub SF Deb 13-3/4% '2000	8212	49a
Amer Health Care Mgmt	Sub Nt 15% '94	8708	41
Anglo Co., Inc.	Gtd Sub SF Deb 11-7/8% '98	8311	49e
Argo Petroleum	Sub SF Deb 16-1/2% '2002	8608	49a
Baldwin-United Corp	Sub SF Deb 10% '2009	8309	26f
BASIX Corp	Sub Deb 11-5/8% '2003	8802	49
Beker Indus.	Ser Sub SF Deb 15-7/8% '2003	8510	14a
Braniff Airways	SF Deb 9-1/8% '97	8205	4
Buttes Gas & Oil	Deb 10-1/4% '97	8511	49a
Charter Co	Sub Deb 10-5/8% '98	8404	49d
Chemetron Corp	SF Deb 9% '94	8802	14b
Coleco Indus.	Sub SF Deb 14-3/8% '2002	8807	40h
Crystal Oil Co	Sub SF Deb 12-5/8% '90	8610	49b
Emons Indus. Inc.	Eq Tr Ctfs Ser 1 11.45% '94	8404	55
First Republic Bank	SF Deb 9-3/8% '2001	8808	10a
Food Fair (Stores)	SF Deb 8-3/8% '96	7810	58c
FSC Corp.	Sr SF Deb 15-3/4% '95	8111	25
Gambles Credit	Sr Notes 9-3/8% '86	8204	26e
Global Marine Inc.	Sr Sub Deb 12-3/8% '98	8601	49e
Hardwicke Co's Inc.	Sub SF Deb 14% '94	8310	40g
Inforex, Inc.	Sub Deb 10-5/8% '98	7910	20b
Itel Corp.	Xs Sub Deb 9-5/8% '98	8101	26f
Johns-Manville	SF Deb 7.85% '2004	8208	13h
Jones & Laughlin Steel	Sub Deb 6-3/4% '94	8607	66a
Lionel Corp.	Sub SF Deb 10-5/8% '99	8202	40h
LTV Corp.	Xs SF Deb 9-1/4% '97	8607	17
Mclean Indus.	Sub Deb 12% '2003	8611	63
Mego Int'l	Sub SF Deb 12-7/8% '94	8206	40h
Michigan General	Xs Sr SF Deb 10-3/4% '98	8704	17a
Mission Ins. Group	SF Deb 9% '2002	8511	35

Table 1--continued

Morton Shoe Cos., Inc	Sr SF Deb 12-3/4% '96	8201	39b
North American Car Corp	Equip Tr. 8.10% '92	8412	55b
Pettibone Corp	Xs Sub SF Deb 12-3/8% '2000	8602	41b
Public Service, New Hamp	1st V 9-1/8% '2006	8801	72a
Radice Corp	Sub SF Deb 14-5/8% '2004	8802	13c
Sharon Steel	Sub SF Deb 14-1/4% '99	8704	66b
Smith Int'l	SF Deb 9.85% '2004	8603	49e
Storage Technology	Nts 10-5/8% '93	8411	20b
Sunbeam Corp	SF Deb 5-1/2% '92	8802	24d
Texaco Capital	Ext'd Nt 13-1/4% '87	8704	26
Texaco Inc	Deb 7-3/4% '2001	8704	49c
Texas Intl Airlines	Xs Sub Deb 10-7/8% '98	8309	4
Todd Shipyards	Sr Sub Nts 14% '96	8708	63
Wedtech Corp	Sr Sub Nts 14% '96	8612	42b
Western Co. No. America	x/s Sub Deb 10-7/8% '97	8802	49e
White Motor Corp	SF Deb 7-1/4% '93	8209	9a
Wickes Corp	SF Deb 6% '92	8204	13d
Wilson Food	Deb 8-3/8% '97	8304	27e

"Ch. 11" indicates the date on which the company filed for Chapter 11. "Ind." indicates the industry classification of the company by Standard & Poor's Bond Guide.

Source: Standard & Poor's Bond Guide.

Table 2. Date of First Bond Downgrade and of Filing for Chapter 11

Company Name	Bond Name	Bef.	After	Date	Ch.11	Ahead
Allegheny Int'l	Sub SF Deb 10.40% '2002	BB-	B+	8510	8802	28
Allis-Chalmers (Mfg) Corp	SF Deb 4.85% '90	A-	BBB+	8109	8706	69
Amarex Inc	Sub SF Deb 13-3/4% '2000	B	CCC	8211	8212	1
Amer Health Care Mgmt	Sub Nt 15% '94	B	D	8706	8708	2
Anglo Co., Inc.	Gtd Sub SF Deb 11-7/8% '98	B+	B	8210	8311	13
Argo Petroleum	Sub SF Deb 16-1/2% '2002	B-	CCC	8311	8608	33
Baldwin-United Corp	Sub SF Deb 10% '2009	BB+	BB-	8204	8309	17
BASIX Corp	Sub Deb 11-5/8% '2003	B	CCC+	8801	8802	1
Beker Indus.	Ser Sub SF Deb 15-7/8% '2003	CCC	D	8508	8510	2
Braniff Airways	SF Deb 9-1/8% '97	BBB-	BB	8004	8205	25
Buttes Gas & Oil	Deb 10-1/4% '97	B	B-	8101	8511	58
Charter Co	Dub Deb 10-5/8% '98	B	B-	8101	8404	39
Chemetron Corp	SF Deb 9% '94	BBB	BBB-	7908	8802	102
Coleco Indus.	Sub SF Deb 14-3/8% '2002	B+	B-	8312	8807	55
Crystal Oil Co	Sub SF Deb 12-5/8% '90	B	B-	8212	8610	46
Emons Indus. Inc.	Eq Tr Ctfs Ser 1 11.45% '94	B	CCC	8206	8404	22
First Republic Bank	SF Deb 9-3/8% '2001	AA	A+	8604	8808	28
Food Fair (Stores)	SF Deb 8-3/8% '96	BB	D	7810	7810	0
FSC Corp	Sr SF Deb 15-3/4% '95	B	CCC	8108	8111	3
Gambles Credit	Sr Notes 9-3/8% '86	A	BBB	7807	8204	45
Global Marine Inc.	Sr Sub Deb 12-3/8% '98	B+	B	8302	8601	11
Hardwicke Co's Inc.	Sub SfDeb 14% '94	CCC	D	8307	8310	3
Inforex, Inc.	Sub Deb 10-5/8% '98	B	D	7910	7910	0
Itel Corp.	Sub Deb 9-5/8% '98	BB	B	7906	8101	19
Johns-Manville	SF Deb 7.85% '2004	AA	A+	8006	8208	26
Jones & Laughlin Steel	Sub Deb 6-3/4% '94	BB-	B	8509	8607	10
Lionel Corp.	Sub SF Deb 10-5/8% '99	B	D	8202	8202	0
LTV Corp.	SF Deb 9-1/4% '97	BB-	B+	8502	8607	17
Mclean Indus.	Sub Deb 12% '2003	B-	D	8607	8611	4
Mego Int'l	Sub SF Deb 12-7/8% '94	B	CCC	8101	8206	9
Michigan General	Xs Sr SF Deb 10-3/4% '98	CCC-	C	8703	8704	1
Mission Ins. Group	SF deb 9% '2002	A	BB+	8408	8511	15

Table 2--continued.

Morton Shoe Cos., Inc	Sr SF Deb 12-3/4% '96	B	D	8201	8201	0
North American Car Corp	Eq Tr. 8.10% '92	BBB	B	8302	8412	22
Pettibone Corp	Xs Sub SF Deb 12-3/8% '2000	BB-	B	8207	8602	43
Public Service, New Hamp	1st V 9-1/8% '2006	BBB	BBB-	8201	8801	72
Radice Corp	Sub SF Deb 14-5/8% '2004	B-	D	8709	8802	5
Sharon Steel	Sub SF Deb 14-1/4% '99	BB	B	8007	8704	81
Smith Int'l	SF Deb 9.85% '2004	A	BBB	8506	8603	9
Storage Technology	Nts 10-5/8% '93	BBB	BB	8402	8411	9
Sunbeam Corp	SF Deb 5-1/2% '92	A	BBB+	8101	8802	85
Texaco Capital	Ext'd Nt 13-1/4% '87	AA-	A+	8505	8704	23
Texaco Inc	Deb 7-3/4% '2001	AA+	AA-	8403	8704	36
Texas Intl Airlines	Sub Deb 10-7/8% '98	B	CCC	8207	8309	14
Todd Shipyards	Sr Sub Nts 14% '96	B-	CC	8705	8708	3
Wedtech Corp	Sr Sub Nts 14% '96	B-	CC	8612	8612	0
Western Co. No. America	Sub Deb 10-7/8% '97	BB-	B-	8306	8802	56
White Motor Corp	SF Deb 7-1/4% '93	B	CCC	8008	8209	21
Wickes Corp	SF Deb 6% '92	BBB	BB	8103	8204	13
Wilson Food	Deb 8-3/8% '97	BB	B	7902	8304	50

"Bef." and "After" are the bond ratings before and after the first bond downgrade. "Date" is the year and month of the first bond downgrade. "Ch. 11" is the year and month in which the company filed for Chapter 11. "Ahead" is the number of months by which the bond downgrade preceded the filing of Chapter 11.

Source: Standard & Poor's Bond Guide.

CHAPTER 4
RESULTS ON FINANCIAL MARKETS AND BANKRUPTCY

For our research on risk premia and bankruptcy, we computed and drew risk premium curves for each of our 50 companies' bonds. (These curves are presented in the Appendix.) A solid line indicates a bond rating change by S&P, a dotted line one by Moody's. The arrows on the graphs indicate a bond upgrade.

In 80% of our sample, or 40 of the risk premium curves, there is a definite upward trend: risk premia rise steadily as the company approaches bankruptcy. Nine (18%) have ambiguous, fluctuating trends, and only one, or 2% of our sample, shows a downward trend where the risk premium on its bond actually fell as it moved towards bankruptcy. Hence, our data suggest that the market generally incorporates the likelihood of bankruptcy adequately in its overall assessment of risk and includes this particular risk in the valuation of securities.

When we compare the relationship between bond rating changes and risk premia curves, we find that for most cases where there was an obviously increasing risk premium, the

rating downgrade came after the risk premium had begun to increase. Hence, in the short-term, a lag of one to seven months does exist. This conclusion confirms that of Weinstein (1977), who found that markets had anticipated bond rating changes 18 to six months before the change. It, however, conflicts with Katz (1974), who concluded that yield-to-maturity adjusted to the rating change six-to-ten weeks after it happened. We believe the reason for this discrepancy is that for measuring market-assessed risk, our risk premium, a relative value, is better than the yield-to-maturity, an absolute value, used by Katz. This is because while factors such as added risk and inflation would eat away the nominal returns of yield-to-maturity and bias the results of any study based on it, risk premium would account for such factors and hence provide an accurate indication of the returns on the bond.

Our data, then, seem to suggest that bond ratings, though popular since the early 1900's, cannot predict risk premium changes or any upcoming default. We believe, however, that the lag phenomenon is not particularly meaningful. For example, a bond downgrade that trails an increase in the risk premium may lead a later increase. Since bond rating changes should warn investors of coming bankruptcy and default, what really matters in the long-run is whether a bond rating provides new information to the market on companies that later went bankrupt. That can be determined only by seeing if bond

rating changes have any impact on the market. Assuming that the first bond downgrade provides the market with the greatest amount of new information about changes in risk, we must further study the impact of the first bond downgrade on the market.

Our data can be used to compare the two rating agencies, S&P and Moody's, to see which warns investors earlier. Table 3 gives the relevant information. On average, S&P gave the first bond downgrade 24.54 months before a company filed for Chapter 11, while Moody's gave the first consistent bond downgrade 21.58 months, or 2.96 months after S&P, before a company filed for Chapter 11. Out of a sample of 50 companies, there were five bonds that received no downgrades whatsoever from S&P's and six that received no downgrades whatsoever from Moody's before the companies which issued them filed for Chapter 11 bankruptcy. Although there was no rating change, the markets did foresee the coming bankruptcy, and the risk premia on these bonds began increasing an average of three to five months before Chapter 11. Finally, six companies which S&P's rated were not rated at all by Moody's. Hence, it would seem that in this specific instance S&P provided more timely and more complete bond ratings and changes than Moody's in the sample and for the period we studied. We emphasize that this is a one-sided test only, and that it by no means can be thought of as a definitive conclusion.

As described earlier in Chapter 3, we divided the sample of companies which filed Chapter 11 into those that later re-organized and those that were liquidated. Nine out of the 50 companies in our sample were "liquidated," while the other 41 re-organized. The average risk premium curves for these two groups are shown in Figure 1. From this graph, we can roughly conclude some interesting patterns. Long before Chapter 11, the companies that would eventually be liquidated had lower risk premia than those which would later re-organize. The two groups had about the same risk premia 41 to 27 months before Chapter 11. Then, as the companies approached bankruptcy, risk premia of companies which were later liquidated rose steadily above those of later re-organized companies.

After performing t-tests with Montgomery's formula for the three periods (65-to-42 months before bankruptcy, 41-to-27 months before bankruptcy, and 26-to-1 months before bankruptcy), however, we found that this was not so. We had tested for the null hypothesis that the means between the two groups during each month were equal. During the first period of 65-to-42 months before bankruptcy, 20 out of 24 (83%) t-tests were significant, and all t values were negative. By our definition for t, this means that the mean values of risk premia for the later liquidated firms are lower than those for later reorganized firms. During the second period, however, 12 out of 15 (80%) t-tests were significant, and 12 of those 15 t-tests were positive. This means, contrary to what might

be discerned from the graph, that the mean values of risk premia for later liquidated and later reorganized firms were different and that the mean risk premia of the later liquidated firms were higher. Hence, although from just looking at a graph we had thought that the differences, which were clearly visible, would not be statistically significant, the t-tests show that this is not so. Finally, during the third period, 19 out of 26 (73%) t-tests are significant, and only one of the 26 was negative. All other t-tests during this final period were positive. This means that during the final period, the mean risk premia of later liquidated firms were also significantly greater than those of the later reorganized firms, as we had expected from looking at the graph. Table 4 gives the means and the t-tests.

This means that the market can sense the coming of liquidation and therefore place an added risk premium to such risk much earlier than the 27 months we had earlier expected.

For our event study of the effects of the bond downgrade on the daily rates of return, we first had to find the exact press release dates of the bond rating changes. We selected only those companies that were listed on the New York or the American Stock Exchanges.[1] Because we could not find relevant data for two continuous years from the COMPUSTAT Daily Return tape for all our companies, some of the observations in our sample had to be dropped. This left us a samples of 22 pair of bankrupt and matching companies. The matching samples have

equivalent downgrades during the same time period, but did not later file Chapter 11. The companies in the two samples are listed in Tables 5 and 6.

Tables 7 through 10 give the statistical results of our event study. In Table 7, the t-statistic for testing the null hypothesis that the average disturbances at event day, $E_1(0)$, equals zero for the Chapter 11 group is -21.81, with 499 degree of freedom. This t-statistic is significant at the 0.5% level. Thus, as expected in the Research Design and Methodology section, the null hypothesis that the average disturbance at the event day for the Chapter 11 group is zero can be strongly rejected. For the matching sample, however, the t-statistic for testing $E_2(0)$ equals zero is -1.45, which is significant only at a marginal level. The negative signs on both the t-statistics mean that bond downgrades negatively affect shareholder wealth.

To see if the means in the Chapter 11 and matching samples are equal, we employ a special t-test (see Montgomery(1984)), which is suitable for cases when we cannot assume equal variances and when the number of observations is less than 30. The t-statistic for testing the equality of two means is -15.545, with 42 degree of freedom. It is significant at the 0.5% level, so the null hypothesis that the two means are equal is rejected. This means that the daily rates of return of companies in the Chapter 11 sample suffered more with bond downgrades than those in the matching sample.

The variances of the two groups, as given by the F-test, were not significantly different.[2]

Table 8 shows the statistical analysis of the two sub-groups in the Chapter 11 sample, the companies which re-organized and those that were liquidated. The t-statistics are -4.98 for companies which later re-organized and -26.94 for companies which did not. Since both are significant, the null hypotheses are rejected. Using Montgomery's formula, we find that the t-test is -0.32 with 9 degree of freedom, which is not significant. Hence, the two means are not statistically significantly different. Finally, the variance of the re-organized companies is lower than that of the companies which were later liquidated.[3]

Tables 9 and 10 give the daily prediction error and cumulative daily prediction errors in the 21 days surrounding the downgrade announcement. Figure 2 shows the cumulative error curves for both the Chapter 11 and the matching samples. These curves show that the rating downgrades had a definite negative impact on the daily rates of return. Most importantly, the relationship between these two curves tells us that the impact of the first bond downgrade is much more severe on companies which would later file for Chapter 11 than those that would not. Hence, we may conclude that the market does react to downward rating changes and that the rating agencies therefore do provide significant new information to the market with rating changes. These results conflict with

those of previous works mentioned in Chapter 2. We believe, however, that the issue is still very much unresolved, as can be seen by the seemingly contradictory results of Griffin and Sanvincente (1982). Therefore, our work should contribute to the ongoing debate.

Notes

1. Our two criteria for selecting companies into the Chapter 11 and matching samples for event study were:

   1. The companies had to be listed either on the New York or the American Stock Exchanges.
   2. There must be two years of continuous data available for the companies.

2. The F-test value is 1.13, with degree of freedom (21, 20). This F-value is not significant, so the variances of the two groups are not significantly different.

3. The F-test value is 8.13 with a positive sign, and it is significant at the 1% level.

Table 3. Dates of Downgrades by S&P and Moody's Compared

Company Name	Bond Name	S&P	Ahead	Moodys	Ahead	Diff.
Allegheny Int'l	Sub SF Deb 10.40% '2002	8510	28	8603	23	5
Allis-Chalmers (Mfg) Corp	SF Deb 4.85% '90	8109	69	8104	74	-5
Amarex Inc	Sub SF Deb 13-3/4% '2000	8211	1	8210	2	-1
Amer Health Care Mgmt	Sub Nt 15% '94	8706	2	8706	2	0
Anglo Co., Inc.	Gtd Sub SF Deb 11-7/8% '98	8210	13	8208	15	-2
Argo Petroleum	Sub SF Deb 16-1/2% '2002	8311	33	8601	7	26
Baldwin-United Corp	Sub SF Deb 10% '2009	8204	17	N/A		
BASIX Corp	Sub Deb 11-5/8% '2003	8801	1	8711	3	-2
Beker Indus.	Ser Sub SF Deb 15-7/8% '2003	8508	2	8510	0	2
Braniff Airways	SF Deb 9-1/8% '97	8004	25	8008	21	4
Buttes Gas & Oil	Deb 10-1/4% '97	8101	58	8209	38	20
Charter Co	Dub Deb 10-5/8% '98	8101	39	8205	23	16
Chemetron Corp	SF Deb 9% '94	7908	102	7710	124	-22
Coleco Indus.	Sub SF Deb 14-3/8% '2002	8312	55	8803	4	51
Crystal Oil Co	Sub SF Deb 12-5/8% '90	8212	46	8210	48	-2
Emons Indus. Inc.	Eq Tr Ctfs Ser 1 11.45% '94	8206	22	8208	20	2
First Republic Bank	SF Deb 9-3/8% '2001	8604	28	8603	29	-1
Food Fair (Stores)	SF Deb 8-3/8% '96	7810	0	N/A		
FSC Corp	Sr SF Deb 15-3/4% '95	8108	3	N/A		
Gambles Credit	Sr Notes 9-3/8% '86	7807	45	N/A		
Global Marine Inc.	Sr Sub Deb 12-3/8% '98	8302	11	8505	8	3
Hardwicke Co's Inc.	Sub SfDeb 14% '94	8307	3	N/A		
Inforex, Inc.	Sub Deb 10-5/8% '98	7910	0	7910	0	0
Itel Corp.	Sub Deb 9-5/8% '98	7906	19	7907	18	1
Johns-Manville	SF Deb 7.85% '2004	8006	26	7904	40	-14
Jones & Laughlin Steel	Sub Deb 6-3/4% '94	8509	10	8503	16	-6
Lionel Corp.	Sub SF Deb 10-5/8% '99	8202	0	8202	0	0
LTV Corp.	SF Deb 9-1/4% '97	8502	17	8607	0	17
Mclean Indus.	Sub Deb 12% '2003	8607	4	8607	4	0
Mego Int'l	Sub SF Deb 12-7/8% '94	8101	9	N/A		
Michigan General	Xs Sr SF Deb 10-3/4% '98	8703	1	8704	0	1
Mission Ins. Group	SF deb 9% '2002	8408	15	8408	15	0

Table 3--continued.

Morton Shoe Cos., Inc	Sr SF Deb 12-3/4% '96	8201	0	8103	10	-10
North American Car Corp	Eq Tr. 8.10% '92	8302	22	8302	22	0
Pettibone Corp	Xs Sub SF Deb 12-3/8% '2000	8207	43	8208	42	1
Public Service, New Hamp	1st V 9-1/8% '2006	8201	72	8208	65	7
Radice Corp	Sub SF Deb 14-5/8% '2004	8709	5	8709	5	0
Sharon Steel	Sub SF Deb 14-1/4% '99	8007	81	8008	80	1
Smith Int'l	SF Deb 9.85% '2004	8506	9	8406	21	-12
Storage Technology	Nts 10-5/8% '93	8402	9	8311	12	-3
Sunbeam Corp	SF Deb 5-1/2% '92	8101	85	8209	65	20
Texaco Capital	Ext'd Nt 13-1/4% '87	8505	23	8512	16	7
Texaco Inc	Deb 7-3/4% '2001	8403	37	8303	49	-12
Texas Intl Airlines	Sub Deb 10-7/8% '98	8207	14	8207	14	0
Todd Shipyards	Sr Sub Nts 14% '96	8705	3	8705	3	0
Wedtech Corp	Sr Sub Nts 14% '96	8612	0	8612	0	0
Western Co. No. America	Sub Deb 10-7/8% '97	8306	56	8211	63	-7
White Motor Corp	SF Deb 7-1/4% '93	8008	1	8009	0	1
Wickes Corp	SF Deb 6% '92	8103	13	8104	12	1
Wilson Food	Deb 8-3/8% '97	7902	50	7710	66	-16

"S&P" and "Moody's" indicate the year and month of the first consistent bond downgrade by S&P and Moody's, respectively. "Ahead" indicates the number of months before bankruptcy that downgrade took place. "Dif." is the number of months between S&P's first consistent downgrade and bankruptcy minus the number of months between Moody's first consistent downgrade and bankruptcy.

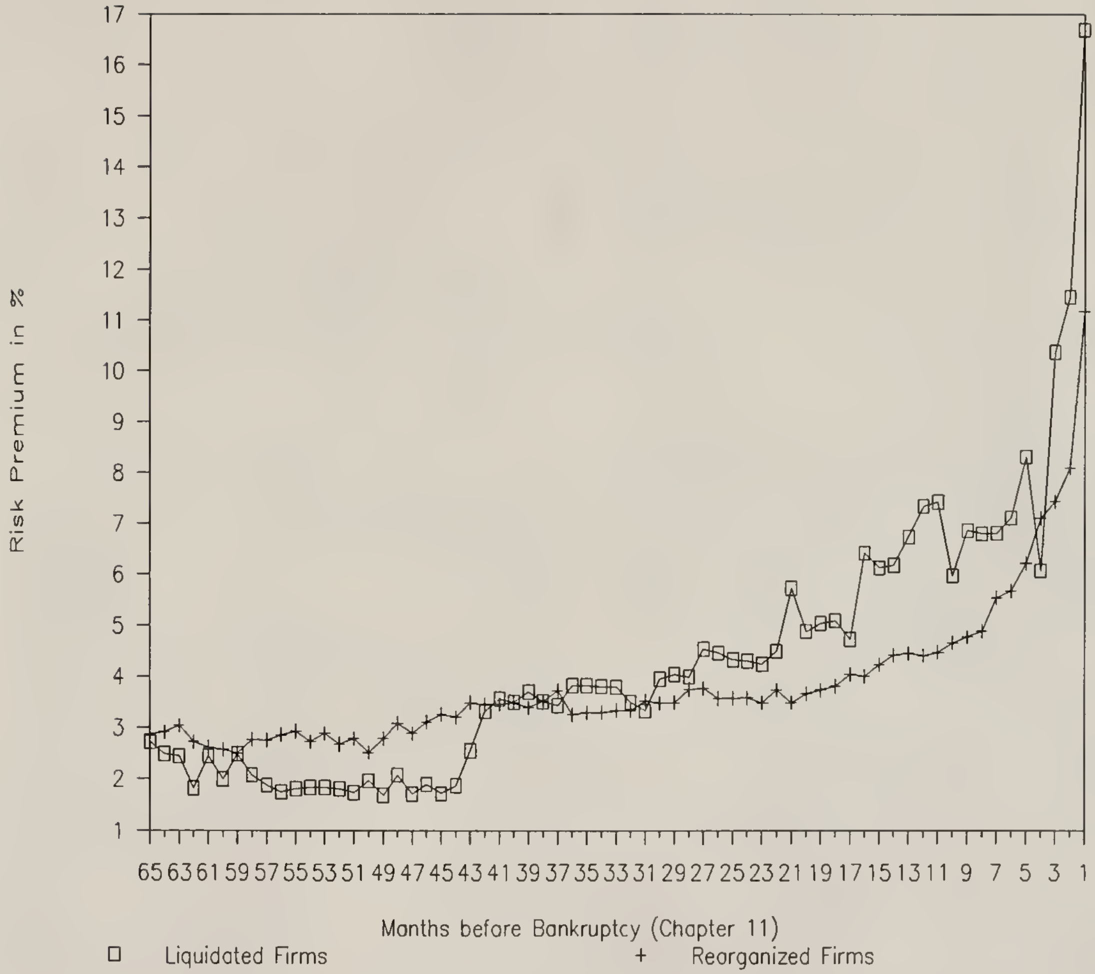


Figure 1. Risk Premia Curves Comparison

Risk premia trends for companies that filed for Chapter 11 and later re-organized versus those that filed and were later liquidated.

Table 4. T-Test of Risk Premia Trends

Time	$Mean_1$	$Mean_2$	Diff.	t-test	s.l.
1	16.70	11.18	5.51858	5.969257	0.5%
2	11.46	8.08	3.37600	3.651703	0.5%
3	10.38	7.43	2.94731	3.188007	0.5%
4	6.08	7.11	-1.02914	-1.113180	
5	8.31	6.22	2.08476	2.255015	2.5%
6	7.12	5.68	1.43333	1.550387	10%
7	6.80	5.55	1.25468	1.357147	10%
8	6.80	4.89	1.90249	2.059800	5%
9	6.86	4.78	2.08516	2.255444	2.5%
10	5.98	4.65	1.32662	1.434954	10%
11	7.42	4.47	2.94818	3.188950	0.5%
12	7.33	4.41	2.92675	3.165763	0.5%
13	6.73	4.45	2.28420	2.470741	2.5%
14	6.19	4.42	1.77084	1.915457	5%
15	6.14	4.23	1.90900	2.064899	5%
16	6.42	4.00	2.42500	2.623039	2.5%
17	4.73	4.04	0.68789	0.744070	
18	5.10	3.81	1.28795	1.393130	10%
19	5.04	3.74	1.30813	1.414961	10%
20	4.88	3.66	1.22106	1.320781	10%
21	5.74	3.49	2.25051	2.434302	2.5%
22	4.49	3.73	0.76234	0.824601	
23	4.23	3.49	0.74654	0.807508	
24	4.32	3.58	0.74654	0.807508	
25	4.32	3.58	0.74759	0.808646	
26	4.46	3.57	0.88553	0.957843	
27	4.54	3.77	0.77331	7.588362	0.5%
28	3.99	3.75	0.24753	2.428966	2.5%
29	4.04	3.49	0.55032	5.400186	0.5%
30	3.95	3.48	0.46810	4.593351	0.5%
31	3.33	3.53	-0.19686	-1.931730	5%
32	3.50	3.34	0.16256	1.595207	10%
33	3.80	3.34	0.45914	4.505502	0.5%
34	3.80	3.30	0.50408	4.946421	0.5%
35	3.83	3.29	0.53727	5.272179	0.5%
36	3.82	3.25	0.56812	5.574928	0.5%
37	3.44	3.72	-0.28775	-2.823640	1%
38	3.51	3.53	-0.01832	-0.179790	
39	3.70	3.39	0.30900	3.032172	1%
40	3.50	3.49	0.01545	0.151591	
41	3.56	3.46	0.10248	1.005648	
42	3.32	3.45	-0.12621	-0.897810	
43	2.56	3.49	-0.93164	-6.627130	0.5%
44	1.87	3.20	-1.32963	-9.458170	0.5%
45	1.72	3.26	-1.53593	-10.925600	0.5%
46	1.89	3.12	-1.22093	-8.684910	0.5%
47	1.71	2.89	-1.17630	-8.367450	0.5%
48	2.08	3.08	-0.99972	-7.111410	0.5%

Table 4--continued.

49	1.68	2.79	-1.10180	-7.837530	0.5%
50	1.97	2.52	-0.55000	-3.912360	0.5%
51	1.74	2.79	-1.04960	-7.466210	0.5%
52	1.80	2.68	-0.87340	-6.212830	0.5%
53	1.84	2.89	-1.04792	-7.454230	0.5%
54	1.84	2.73	-0.88565	-6.299980	0.5%
55	1.80	2.93	-10.14058	-7.996630	0.5%
56	1.74	2.86	-1.11917	-7.961060	0.5%
57	1.88	2.76	-0.87986	-6.258740	0.5%
58	2.08	2.77	-0.69457	-4.940710	0.5%
59	2.49	2.50	-0.10409	-0.100230	
60	2.00	2.57	-0.57091	-4.061090	0.5%
61	2.45	2.62	-0.17650	-1.255510	
62	1.83	2.73	-0.89842	-6.390810	0.5%
63	2.45	3.04	-0.58684	-4.174430	0.5%
64	2.49	2.91	-0.42263	-3.006340	1%
65	2.72	2.87	-0.14889	-1.059100	

"Mean_1 and Mean_2" are the risk premia means for the later liquidated and later reorganized firms, respectively. "Diff." is their difference. "t-test" is the value of the t-test, and "s.l." is the significance level.

Table 5. Sample of Bankrupt (Chapter 11) Companies for Event Study

M.#	Company Name	Bond Name	CUSIP	Bef.	After	Event	Ind
2	Johns-Manville	SF Deb 7.85% '2004	565020	AA	A+	800620	13h
3	Sharon Steel	Sub SF Deb 14-1/4% '99	819785	BB	B	800708	66b
4	Braniff Airways	SF Deb 9-1/8% '97	105425	BBB-	BB	800407	4
7	Allegheny Int'l	Sub SF Deb 10.40% '2002	17372	BB-	B+	851009	17a
11	Public Service, N.H.	1st V 9-1/8% '2006	744482	BBB	BBB-	820118	72a
12	Smith Int'l	SF Deb 9.85% '2004	832110	A	BBB	850606	49e
13	White Motor Corp	SF Deb 7-1/4% '93	964066	B	CCC	800808	9a
17	Mego Int'l	Sub SF Deb 12-7/8% '94	585163	B	CCC	810109	40h
20	Allis-Chalmers Corp	SF Deb 4.85% '90	19645	A-	BBB+	810909	41
22	Itel Corp.	Sub Deb 9-5/8% '98	465640	BB	B	790629	26f
23	Sunbean Corp	SF Deb 5-1/2% '92	867068	A	BBB+	810127	24d
24	Baldwin-United Corp	Sub SF Deb 10% '2009	58319	BB+	BB-	820429	26f
26	Argo Petroleum	Sub SF Deb 16-1/2% '2002	40138	B-	CCC	831114	49a
28	Charter Co	Dub Deb 10-5/8% '98	161177	B	B-	810123	49d
30	Buttes Gas & Oil	Deb 10-1/4% '97	124187	B	B-	810122	49a
34	LTV Corp.	SF Deb 9-1/4% '97	502210	BB-	B+	850228	17
36	Wedtech Corp	Sr Sub Nts 14% '96	948462	B-	CC	861205	42b
37	Todd Shipyards	Sr Sub Nts 14% '96	889039	B-	CC	870528	63
38	Global Marine Inc.	Sr Sub Deb 12-3/8% '98	379352	B+	B	830211	49e
39	Anglo Co., Inc.	Gtd Sub SF Deb 11-7/8% '98	35053	B+	B	821013	49a
40	Coleco Indus.	Sub SF Deb 14-3/8% '2002	193378	B+	B-	831221	40h
41	Western Co. No. Am.	Sub Deb 10-7/8% '92	958043	BB-	B-	830627	49e

Data in both Tables 4 and 5 are matched. "M. #" is the matching number. "CUSIP" is the identification number of the company on COMPUSTAT. "Bef.," "After," and "Event" are the rating before and after and the precise year, month, and date of the rating downgrade. "Ind." is the industry classification code.

Table 6. Matching Sample for Event Study of Bond Downgrades

M.#	Company Name	CNUM	Bond Name	Bef.	After	Event	Ind.
2	Black & Decker Mfg	91797	Notes 8.45% 1985	AA	A+	8104	13e
3	Keystone Consol Indus.	493422	SF Deb 7-1/4% 1993	BB	B	8203	66d
4	MCorp	55267M	SF Deb 9-3/8% 2001	BBB-	BB	8708	10a
7	Blair & Co.	92815	Sub Sf Deb 13-5/8% '98	BB-	B+	8410	30a
11	Kansas Gas & Elec	485260	1st Mtg 9-5/8% 2005	BBB	BBB-	8206	72a
12	Hundson Bay Mining&Smelting	443654	SF Deb 10-1/2% 1995	A	BBB	8206	45a
13	Int'l Harvester Co.	638901	SF Deb 8-5/8% 1995	B	CCC	8206	9a
17	Filmways	686285	Sub Deb 11% 1998	B	CCC	8102	53a
20	Heileman (G) Brewing	422884	SF Deb 11-5/8% 2005	A-	BBB+	8508	11a
22	Chrysler Corp	171196	SF Deb 8% 1998	BB	B	7909	26a
23	Boise Cascade	97383	Notes 10.45% 1990	A	BBB+	8207	13d
24	U.S. Home	912061	Notes 10% 1987	BB+	BB-	8203	13c
26	Campanelli Industries	134024	SrSubSF Deb 12-3/8% '94	B-	CCC	8208	38
28	Genesco	371532	Sr SF Notes 14-1/4% '94	B	B-	8310	58
30	Zapata Corp	989070	Sub Deb 10-1/4% '97	B	B-	8512	17a
34	MGM Grand Hotels	553012	Sub Sf Deb 10% 94	BB-	B+	8102	40g
36	Oak Indus	671400	SF Deb, 13.65% 2001	B-	CC	8503	12
37	Cannon Group	137726	Sr Sub Deb 12-7/8% 2001	B-	CC	8708	47
38	Josephson Int'l	481021	Sub SF Deb 12-1/2% 2003	B+	B	8509	62
39	MDC Holdings	552676	Sub Notes 7% '93	B+	B	8606	13c
40	Angeles Corp	34624	Sr Sub Deb, 12-1/2% '95	B+	B-	8705	61
41	Coastal Corp	190441	SubEx V/RNt 14.6% '94	BB-	B-	8506	49

"M. #" is the matching number for the data in Tables 4 and 5. "CNUM" is the identification code of the company on COMPUSTAT.

Table 7. T-test for Chapter 11 (bankrupt) and Matching Samples: Event Study Results

Chapter 11 Sample		Matching Sample	
$E_1(0)$	-0.03199700	$E_2(0)$	-0.00203900
Std.	0.00687700	Std.	0.00645500
H_0: $E_1(0) = 0$, $t_1 = -21.98^*$ (d.f. = 499, significant at 0.5%)		H_0: $E_2(0) = 0$, $t_2 = -1.45^*$ (d.f. = 499, significant at 10%)	

H_0: $E_1(0) = E_2(0)$
t-test = -15.545^* (d.f.= 42)
(significant at 0.5%)

Table 8. T-test for Sub-Groups of Chapter 11 Companies: Those which were Liquidated and those which Reorganized

Liquidated Group		Reorganized Group	
$E_1(0)$	-0.03293800	$E_2(0)$	-0.02922600
Std.	0.01980400	Std.	0.00694700
H_0: $E_1(0) = 0$,		H_0: $E_2(0) = 0$,	
$t_1 = -4.98^*$		$t_2 = -26.94^*$	
(d.f.: 499,		(d.f.: 499,	
significant at 0.5%)		significant at 0.5%)	

H_0: $E_1(0) = E_2(0)$
t-test = -0.32 (d.f.: 9)

Table 9. Disturbance Resulting from Bond Downgrade on Chapter 11 (Bankrupt Sample) and Statistical Analysis

Event Day	avg E(t) (%)	CE (%)
-10	-0.006464	-0.006464
- 9	-0.007603	-0.014067
- 8	-0.001908	-0.015975
- 7	-0.001019	-0.016994
- 6	-0.016982	-0.033976
- 5	0.001227	-0.032749
- 4	-0.002338	-0.035087
- 3	-0.005651	-0.040738
- 2	-0.007840	-0.048578
- 1	-0.009647	-0.058225
0	-0.031997	-0.090222
1	0.018805	-0.071417
2	0.022623	-0.048794
3	0.002346	-0.046448
4	0.002065	-0.044383
5	-0.008776	-0.053159
6	-0.034234	-0.087393
7	0.014345	-0.073048
8	-0.029843	-0.102891
9	0.021802	-0.081089
10	-0.008666	-0.089755

Variable	Value(%)	t-statistic
E(-1)	-0.009674	-1.41 * 10.0%
E(0)	-0.031997	-4.65 * 1.0%
CE(-10,0)	-0.090222	-3.38 * 0.5%
CE(-5,0)	-0.056246	-2.11 * 2.5%
CE(-3,0)	-0.055135	-2.06 * 2.5%
CE(-1,0)	-0.041644	-1.56 * 10.0%
CE(+1,0)	-0.013192	-0.49
CE(+3,0)	0.011777	0.44
CE(+5,0)	0.005066	0.19
CE(+10,0)	-0.031530	-1.18
CE(-10,10)	-0.089755	-3.36 * 0.5%

The t-test for CE is:

$$t = CE*(N^{1/2})/(Std(CE)*(T^{1/2}))$$

Table 10. Disturbance Resulting from Bond Downgrade on Matching Sample and Statistical Analysis

Event Day	avg E(t) (%)	CE (%)
-10	-0.012418	-0.012418
- 9	-0.022204	-0.034622
- 8	0.018645	-0.015977
- 7	0.003892	-0.012085
- 6	0.010662	-0.001423
- 5	0.004340	0.002917
- 4	0.013230	0.016147
- 3	0.005412	0.021559
- 2	-0.010702	0.010857
- 1	0.002165	0.013022
0	-0.002039	0.010983
1	0.007029	0.018012
2	-0.000817	0.017195
3	-0.019285	-0.002090
4	0.001402	-0.000688
5	-0.003376	-0.004064
6	-0.000191	-0.004255
7	0.001111	-0.003144
8	0.005467	0.002323
9	0.004831	0.007154
10	-0.004599	0.002555

Variable	Value (%)	t-statistic	
E(-1)	0.002165	0.34	
E(0)	-0.002039	-0.32	
CE(-10,0)	0.010983	1.13	
CE(-5,0)	0.012406	1.28	
CE(-3,0)	-0.005164	-0.53	
CE(-1,0)	0.000126	0.01	
CE(+1,0)	0.004990	0.51	
CE(+3,0)	-0.015112	-1.56	* 10.0%
CE(+5,0)	-0.017086	-1.76	* 5.0%
CE(+10,0)	-0.010467	-1.08	
CE(-10,10)	0.002555	0.26	

The t-test for CE is:

$$t = CE*(N^{1/2})/(Std(CE)*(T^{1/2}))$$

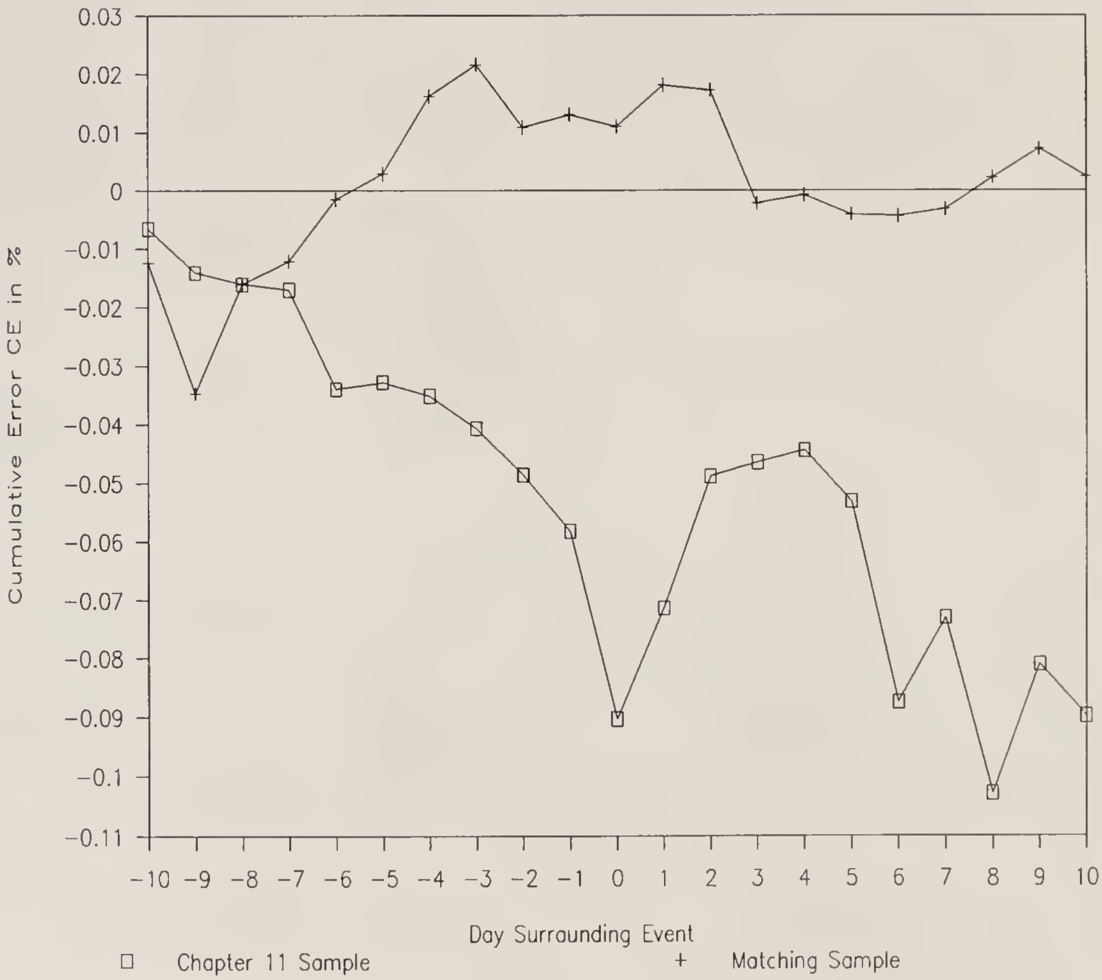


Figure 2. Disturbance Due to Bond Downgrade

This graph compares the disturbance caused by a bond downgrade on companies in the sample which filed for Chapter 11 and in the sample which did not file for bankruptcy.

CHAPTER 5
EMPIRICAL MODEL OF BANKRUPTCY

The evidence that bond rating downgrades provide new information to the market suggests that proper analysis of fundamental corporate factors, such as the ones presumably used by S&P's and Moody's, can give an early warning of impending financial difficulties. Even so, there are at least four problems with using bond downgrades as the sole or primary indicator of bankruptcy risk. First, many firms whose bonds are downgraded never experience significant financial stress. In fact, a company may simply be trying to modify its risk-return balance and better reposition itself in the market place to capitalize on future opportunities. Second, although our event study identified a differential effect between the companies that eventually filed for protection under Chapter 11 of the bankruptcy code and those which did not have to seek protection, that does not mean we can easily tell between the two before the fact. In other words, how much of a difference is "significant?" Third, S&P's and Moody's sometimes give conflicting signals, and there have been cases where the downgrade either does not predate the bankruptcy filing by

very much time or there is no downgrade at all. Finally, it appears that consistent signals start appearing only approximately two years ahead of the Chapter 11 filing, assuming, of course, that they can be correctly interpreted. Thus, bond downgrades give us about as much forewarning as the ZETA model of Altman et al., and the latter model is probably more a practical predictor of bankruptcy than bond downgrades.

Hence, we believe that proper analysis of fundamental corporate characteristics would provide us with a more effective empirical model which could determine bankruptcy risk. What we would need is an indicator which can alert investors and managers of developing circumstances that would normally lead to increased probabilities of bankruptcy long before it actually becomes necessary to file for protection under Chapter 11. Such an indicator would allow investors to make more informed portfolio allocation decisions, and it would signal to corporate managers that corrective actions need to be taken before financial difficulties become serious. We believe that if such an indicator can be found and used to predict financial distress and possible bankruptcy up to five years ahead of potential bankruptcy, then the scarce resources in the economy can be better allocated.

Current bankruptcy prediction models, however, have not shown that they can reliably forecast bankruptcy risk more than two years ahead of filing of Chapter 11. In fact, there is very little evidence to date that it is even possible to

detect the roots of financial distress up to five years ahead of an actual crisis. Our main purpose in this part of the dissertation, then, is to explore this issue: can a bankruptcy prediction model be designed that maintains significant forecasting powers up to five years ahead of the date of Chapter 11 filing? While we would also like to develop a model that can surpass the predictive powers of the ZETA model in the short-run while also preserving that power over five years, we do not, in this dissertation, intend to search specifically for such a "best" model. That task will be left for future research after we have shown that it is possible to maintain high levels of accuracy over the long-run.

Present-day finance literature does not provide us with many works that have looked at the relationship between various types of risk, such as bankruptcy risk, and companies' fundamental characteristics. Zavgren (1985) provides some evidence that asset efficiency is an important indicator which may be of use to us, but we believe that other variables would also be needed. Derkinderen and Crum (1988) developed a framework known as the Potential and Resilience Evaluation (PARE) model on the issues of long-term risk-return balance. This framework suggests some possible variables which can be used to assess the fundamental and strategically crucial characteristics of a company. Basing our views from such a fundamental perspective, as suggested by Derkinderen and Crum (1988) and Zavgren (1985), we have arrived at a list of eight

variables which can assess both the short- and long-run dimensions of the bankruptcy problem. We now turn to a discussion of these variables and the roles they would play in our study of long-term bankruptcy risk.

Variable Definitions

We selected our eight variables out of many potential candidates. In selecting them, we aimed to find the minimum number of factors that together provide signals about both short- and long-run aspects of the companies, in isolation as well as relative to other companies in their core industry. Our reasons for selecting these variables were also partially based on the availability of data, although these variables are considered to be good indicators of differences between the more successful companies and those with lackluster performance records. These variables can roughly be divided into two groups: 1). those which assess company operating and profitability characteristics (which will be referred to as "the Group I variables"), and 2). those which assess fundamental company characteristics (which will be referred to as "the Group II variables.") Existing bankruptcy prediction models focus mostly on relationships that would be included in the first group. Although these factors are obviously important to bankruptcy, particularly in the short-run, we contend that the second group must also be considered if the model is to have adequate long-term predictive powers.

Four variables are included in Group I to measure the company's financial and operating positions. The first is return on assets, or ROA, defined as EBIT/TA. This is the basic earning power ratio and is a strong signal of profitability. We consider that it is a particularly good representation of the company's performance in implementing growth in the past. The second variable in this category is the fixed charge coverage ratio, FCC. This ratio measures simultaneously a company's level of debt and how well its cash flow covers the servicing requirements of debt. It is one of the most important indicators of the ability of the firm to survive adversity in the short-run. The third variable is the market-to-book ratio. The market-to-book ratio measures investors' confidence in the firm and, as a direct result, how well the company can tap into the equity market for capital. In other words, this ratio indicates the extent to which investors believe that the firm has good growth opportunities for the future. A ratio greater than one indicates that the return from reinvested earnings is expected to exceed the required rate of return. Finally, the balance ratio of income and sales, defined as the difference between the growth rates of income and sales, focuses on the profitability of incremental sales. It measures whether the company is boosting sales at the expense of profits and, therefore, may be heading into financial problems even as it continues to expand market share.

To assess the second category of difference indicators, the Group II variables which measure company fundamental characteristics, four additional variables are used. First, ownership assesses the agency effects of the company's management. According to the agency theory literature, such as Jensen and Meckling (1976), when the shareholders contract with the management for the latter to serve the former as agents, some cost is inevitably involved, including a dead-weight loss. This cost occurs because management and shareholders in most corporations (particularly the larger ones) are usually distinctly separate groups, and they likely have differing, even conflicting, interests. For example, management of America's top 200 firms own only 0.1 percent of their companies' stock, and nearly one out of ten Fortune 500 Chief Executive Officers own no stock at all in their companies. Because of such low ownership stakes, many scholars have questioned whether such managements really serve the shareholders' interests. As a result of questions such as this, management ownership has become a topic of interest and discussion in recent years. We agree that this topic is important and relevant to our needs in this dissertation. We believe, however, that absolute ownership measures are not as significant as the net transfer of ownership, which measures whether management, as a whole, increased or decreased its ownership share of the corporation during a period of time. Assuming that management has information the average

shareholder does not, then whether a management is a net purchaser or a net seller of the company's stock shows management's confidence in its own projects. Further, it also shows whether management is committed to the success of the company or whether it is simply "grabbing for parachutes." To incorporate these ideas into the model, we include the net rate of management stock acquisitions as a variable, defined as the difference between management purchases and sales of the company's stock, measured in percentages of total equity.

The second variable in this category is the capital intensity ratio, defined as total assets divided by sales. This ratio measures how much a company must invest in assets to expand its sales. Thus, it indirectly tells us both the structure of the industry and how much the company will have to rely on fresh capital to fuel growth. In this dissertation, though, we do not follow the traditional definitions of industry as given by COMPUSTAT or Dun & Bradstreet. Rather, developing from the ideas of Tse (1987), we regroup the COMPUSTAT SIC codes so as to define 24 lines of industry by the nature of the business. These definitions of industry, along with the growth rate and bankruptcy rate of each industry, are presented in Table 11. As Table 11 and Figure 3 show, a company's line of business does impact significantly on bankruptcy. While the specialty manufacturing industry (code #19) had a 13% cumulative bankruptcy rate during the 1968-1987 period, the chemicals

(code #4) and utilities (code #20) industries suffered only about a 1% cumulative bankruptcy rate during the same period.

Expanding on the information about competitiveness contained in the industry characteristics, and to assess a company's position within its industry, we employ the relative sales growth ratio. This ratio is the difference between the sales growth rate for the primary or core industry in which the company competes and the rate of growth of the company's sales. It indicates the competitiveness of the company within its major industry in terms of its ability to gain market share. It also complements the balance ratio of income and sales, the Group I variable that measures whether the company has gained market share at the expense of profit margins.

The final variable in the Group II variables set is the relatedness ratio, as described by Rumelt (1982). This variable assesses a company's diversification program in that it indicates the extent to which the company focuses its efforts on a portfolio of related businesses that could be expected to have synergistic interdependencies. It is calculated as:

$$\frac{(\text{\% of assets in related segments})}{(\text{number of segments})} \times (\text{number of segments} - 1)$$

and determines whether a company is a "single business" (a value of zero), "unrelated diversified" (a low positive value), or "related diversified" (a high positive value). As Rumelt (1980) points out, different strategies of

diversification can strongly affect a company's long-term prospects, and the degree of relatedness should assess the benefits of those diversifications. According to Rumelt, the higher the relatedness ratio the greater the chances of good performance.

The eight variables described above cover the two broad categories and also collectively address the various dimensions of the PARE framework, which are: 1) the extent to which the firm has good growth opportunities available; 2) whether or not the market perceives that the company can exploit the growth opportunities successfully; 3) the degree to which the fortunes of the firm are subject to foreseeable adversities in the future; 4) whether or not the firm has the ability to survive such adversities.

Role of Variables in the Model

The model of bankruptcy risk developed in this dissertation includes the eight variables discussed above and uses them to derive a summed probability of bankruptcy. Using Logist Analysis, which will be discussed in Chapter 6, a probabilistic function of a cumulative score of z is derived which, in turn, is composed of these eight factors:

$$P = f(z), \text{ where } f' > 0.$$

$$z = a_0 + b_1X_1 + b_2X_2 + \ldots + b_8X_8,$$

where $b_{1..8}$ are coefficients,
X_1 is ROA (EBIT/TA),
X_2 is FCC,
X_3 is Balance Ratio,
X_4 is Market/Book Ratio,
X_5 is Relatedness Ratio,

X_6 is Net Rate of Management Stock Acquisitions,
X_7 is Relative Sales Growth Rate,
X_8 is Capital Intensity.

Hypotheses

Because the methodology used in this dissertation, Logist Analysis (discussed in Chapter 6), develops a model in which the coefficients can reveal the role each variable plays, we can hypothesize about how each factor in the model affects overall assessment of bankruptcy risk. Specifically, according to our model, a negative beta means that the larger the variable, the less the chance of bankruptcy. Similarly, a positive beta means that the larger the variable, the greater the chance of bankruptcy. If any of the variables are able to take on negative values, the rules given above about the sign of the coefficient should be reversed. We hypothesize that all coefficients b_1 through b_8 should be negative.

The coefficients for return on assets, fixed charge coverage, and the market-to-book ratio should be obvious. In principle, the sales-income balance ratio's coefficient is negative because if income is growing more briskly than sales, then the company is experiencing widening profit margins, which would inevitably lead to higher profitability and even more growth in the future. Since long-term considerations sometimes make it necessary to sacrifice short-run profitability to drive out the competition and gain market

share, however, even good, solid companies may have negative values for this ratio. Hence, our confidence about the sign of this particular coefficient is less than for those of the first three variables. More important than the sign, though, is the idea that the balance ratio for the bankrupt companies should be significantly different than the ratio for non-bankrupt companies.

The relatedness ratio's coefficient is negative because a larger relatedness ratio indicates that a company is diversified into related lines of business, which means, as Rumelt (1982) shows, that the company will be able to achieve real product synergy and counter-cyclicality. The net rate of stock acquisition is also expected to be negative because that signals net purchase of stock by management. This is a signal that management expects the firm to be profitable in the long-run.

The coefficient for b_7, relative sales growth, is negative because we expect that companies with good relative sales growth rate will have a negative value for the variable, and a negative coefficient is needed to reverse the impact on the chances of bankruptcy. Finally, the sign of the coefficient for capital intensity is negative because, as Ohlson (1980) points out, larger capital intensity is associated with larger company size, and larger industrial companies do not go bankrupt as easily as smaller ones. On the other hand, though, to the extent that the reciprocal of

the capital intensity ratio is an indicator of asset efficiency, the negative sign would be counter to the findings of Zavgren (1985).

Table 11. Industry Classification, Growth and Bankruptcy Rates

Industry Number	Industry	COMPUSTAT SIC	Growth Rate	Bankruptcy Rate
1	Food	2000-2199	8.94%	2.3622%
2	Clothing & Textiles	2200-2399	5.41%	8.1633%
3	Paper & Publishing	2600-2799	9.51%	3.9130%
4	Chemicals	2800-2839, 2840-2899	10.84%	1.1062%
5	Drugs	2830-2839	11.42%	N/A
6	Petroleum Refining	2900-2999	12.82%	1.6393%
7	Rubber & Leather	3000-3199	5.33%	0.9788%
8	Glass & Cement	3200-3299	7.45%	2.5000%
9	Metals	3300-3499	6.28%	3.3898%
10	Industrial Machinery	3500-3569, 3580-3599	6.33%	2.3490%
11	Office Machinery & Electronic Equipment	3570-3579, 3650-3679	8.71%	6.8452%
12	Electrical Equipment	3680-3699	14.38%	8.7805%
13	Motor Vehicles	3700-3799	7.96%	6.2201%
14	Scientific & Surveying Equipment	3800-3899	8.58%	3.9474%
15	Transportation	4000-4599, 4700-4799	11.20%	11.2245%
16	Agriculture	0100-0999	10.42%	2.6316%
17	Extractive	1000-1499	10.48%	5.4217%
18	Construction	1500-1799, 2400-2499	9.93%	5.2239%
19	Specialty Manuf.	3900-3999	7.02%	13.0435%
20	Utilities	4800-4899	14.37%	1.3245%
21	Wholesale	5000-5199	10.51%	6.5421%
22	Consumer Products	5200-5999	8.78%	4.4983%
23	Services	7000-8999	12.39%	3.7516%
24	Financial	6000-6799	19.00%	2.5097%

Growth Rate is the average annual growth rate of the industry between 1968 and 1987. Bankruptcy Rate is the percentage of businesses that failed during that period.

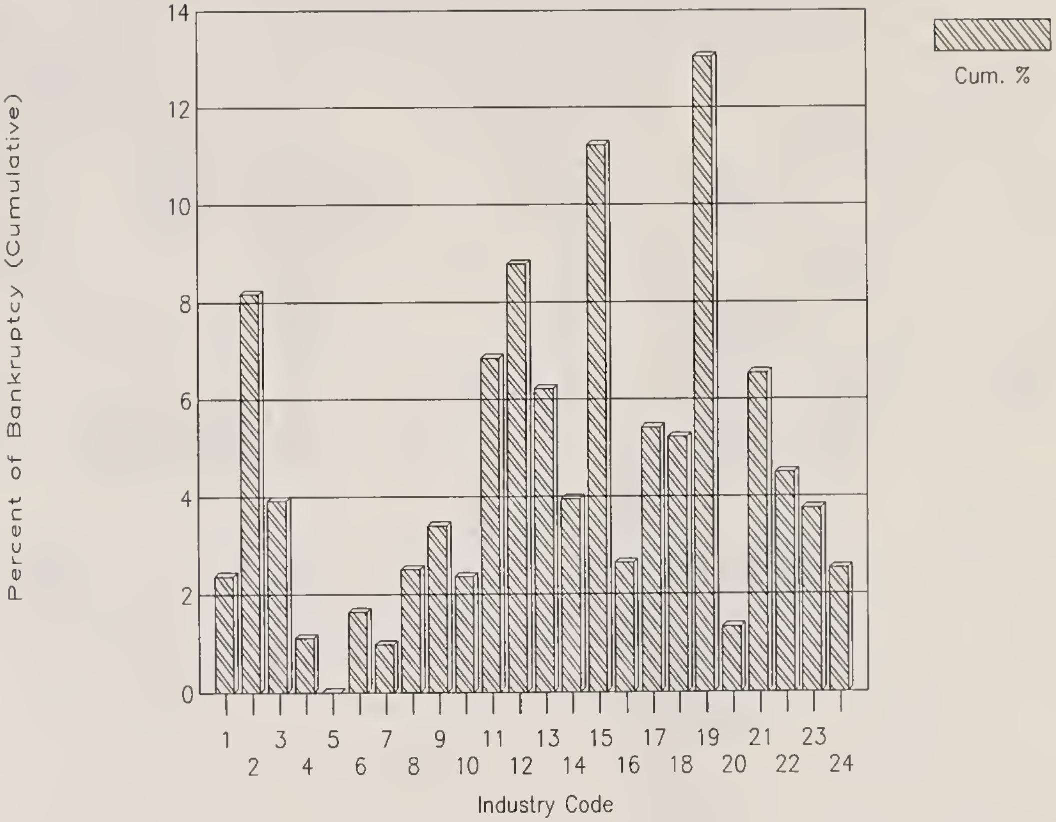


Figure 3. Industry and Bankruptcy Rate

CHAPTER 6
METHODOLOGY TO TEST EMPIRICAL MODEL

The Logist Analysis Methodology

The methodology used in this dissertation to build the empirical bankruptcy model is logist analysis.

Logist analysis is a statistical method that computes the conditional probability that a given observation belongs to a particular class of observations if certain variables about the observation are known. Based on a cumulative probability function, this model does not require that independent variables be multivariate normals or that the classes have equal covariance matrices. Instead, the model is solved using the maximum likelihood method. Thus, logist analysis reduces the fundamental bankruptcy estimation problem to the following: given that a company belongs to some pre-specified population, what is the probability that this company will fail within some pre-specified period of time?

Ohlson (1980), which was discussed earlier in the Literature Review section, was probably the first work on bankruptcy to use logist analysis. Although the research did

not produce a significantly viable model, the work nevertheless provided some interesting insights into the use of logist analysis for empirical studies of bankruptcy. In Ohlson's model, X_i denoted a vector of predictors for company i, β denoted a vector of unknown parameters, and $P(X_i, \beta)$, where P is a probability function $(0 \leq P \leq 1)$, denoted the probability of bankruptcy for a given set of vectors X_i and β. The logarithm of the likelihood of any specific outcome, as reflected by the binary sample space of bankruptcy versus non-bankruptcy, is given by:

$$L(\beta) = \Sigma \log P(X_i, \beta) + \Sigma \log (1 - P(X_j, \beta)),$$

where i, j are elements of the S_1 index set of bankrupt companies and S_2 index set of non-bankrupt companies, respectively. For any specified function P, the maximum likelihood estimates of $\beta_1, \beta_2, \ldots \beta_n$ are obtained by solving:

$$\max_\beta L(\beta).$$

Because we do not as yet have a full theory of bankruptcy, however, we cannot easily find an appropriate class of functions P. As a practical matter, therefore, we can only select a function for the sake of computational and interpretative simplicity. One such function is the logistic function:

$$P = (1 + \exp\{-y_i\})^{-1},$$

where $y_i = \Sigma \beta_j X_{ij} = \beta' X_i$.

This formula has two implications. First, P is increasing in y. Second, y is equal to log (P / (1 - P)).

Like discriminant analysis, logist analysis weights the independent variables and creates a score for each company. The Z score obtained may be used to determine the probability of membership in a group where:

$$\text{Probability of bankruptcy} = 1 / (1 + \exp(-z)) = 1 / (1 + \exp(-a + b_1X_1 + \ldots + b_pX_p)).$$

The b coefficients are weighted so as to maximize the joint probability of bankruptcy for the known bankrupt companies and the probability of non-bankruptcy for those companies that did not go bankrupt. Unlike the coefficients derived from discriminant analysis, these coefficients tell us the role that each individual variable plays in the overall empirical model. Therefore, we can use them to analyze which factors are the most significant in long-term bankruptcy forecasts.

Logist versus Discriminant Analysis

Much previous bankruptcy work, most significantly Altman et al. (1977), has employed the traditional linear discriminant analysis, although both the linear and the quadratic forms have been used. For our dissertation, though, we consider that logist analysis can yield a superior model because logist analysis does not share many of the problems faced by discriminant analysis.

First, linear discrimination is basically a multivariate technique that assigns a score to each element in a sample

using a linear combination of independent variables. The multivariate approach is very appealing because it reduces several financial dimensions of a problem to a single score. In general, such reductions have been quite successful. The bankruptcy models derived from discriminant analysis tend to have high classification accuracies, at least in the short- to medium-terms. Serious questions, however, have been raised about whether so many factors and dimensions of a complex financial problem like bankruptcy can validly be reduced to a single score, or whether crucial information would be lost during the process of such a reduction.

Second, discriminant analysis has several statistical requirements that are difficult to meet for most samples. For discriminant analysis to work, the independent variables must be multivariate normals, and the covariance matrices of the original and hold-out groups must be equivalent. In practice, satisfying both assumptions is difficult. The requirement that the independent variables have multivariate normal distributions, for example, is frequently violated. It will be violated whenever a dummy independent variable, such as the time variable t, is used. Although some remedial measures, such as log transformations, square root transformations, and elimination of outliers can be used, such methods have unclear economic implications which are often too easily ignored. Further, in many cases the requirement that covariance matrices be equal is also violated. This means

that the group covariances are not statistically equivalent, as indicated by Box's F statistic.

A way to avoid the latter problem of unequal covariances is to use quadratic discriminant analysis. Unlike linear discrimination, the quadratic form does not require that covariances must be equal. Instead, quadratic discriminant analysis assesses the covariance of each group independently as it builds a model. The problem, however, is that quadratic discriminant analysis is not nearly as widely used as linear discriminant analysis, and there are also questions about its model-building powers. Altman et al. (1977) and Marks and Dunn (1974) both reported that linear discriminant analysis could achieve greater classification success than quadratic discriminant analysis. The Marks and Dunn paper reached this conclusion for samples where the group variances are similar, the group means are far apart, the sample sizes are small, and the number of variables is small. Although these two papers do not conclusively show that linear discriminant analysis is superior to quadratic discriminant analysis, they suggest that there are significant problems with using the latter to build an empirical model of bankruptcy.

We use the logist analysis method because it resolves both major problems of discriminant analysis. First, unlike discriminant analysis, it does not reduce all the financial dimensions of bankruptcy to a single cut-off score. Rather, it assesses each relevant independent variable and comes up

with a probability of bankruptcy, so that, given that a company belongs to a certain sample, logist analysis provides the probability of failure. Second, unlike linear discriminant analysis, logist analysis does not require that the independent variables be multivariate normals or that groups have equal covariance matrices. Harrell and Lee (1985) reported that even when all the assumptions of discriminant analysis are met, logist analysis is at least as effective as discriminant analysis. Hence, our results should be much more significant than under discriminant analysis. Furthermore, unlike the quadratic version of discriminant analysis, logist analysis is a sound, proven technique that can provide good classification accuracy.

Therefore, we believe that the logist analysis methodology is significantly superior to discriminant analysis for our research. For this reason, we employ it to build our empirical model of bankruptcy.

Sample Design

Logist analysis in our research requires two groups of companies, a bankrupt and a matching sample. Companies that were on the COMPUSTAT Research Tape and which filed for Chapter 11 between 1968 and 1987 are used as our bankrupt companies sample. We select a matching sample of companies in the same industries and with similar asset sizes but that avoided bankruptcy.

Our data come from several sources. We use the COMPUSTAT Research Tape and Industry Tape for basic data on financial variables of both our samples. The COMPUSTAT Research Tape provides such data for the bankrupt sample, while the Industry Tape provides such data for our matching sample. We use the Ownership Reporting System Tape, published by the National Archives and Record Services, to obtain data on the management acquisition of company stock. Next, we use the COMPUSTAT Segments Information Tape to find the segments of our companies and to compute their degree of diversification. Finally, we use the COMPUSTAT Research and COMPUSTAT Industry tapes again to calculate industry growth and bankruptcy rates.

At the start, we had 315 bankrupt companies that were deleted from the COMPUSTAT Industry Tape and moved to the COMPUSTAT Research Tape between 1968 and 1987 by a deletion code of 02, which indicates bankruptcy. We could not, however, find 5 years of continuous data for all 315 companies because the information we needed was on several different tapes, each of which had information on different time periods. The COMPUSTAT Business Segments Information Tape, for example, has data only from 1975 onward, as does the Ownership Reporting System. The Master Current Tape of Ownership Reporting System, however, offers data from January 1980 to August 1987, and the Master History Tape offers data from January 1975 to April 1982. Even though we used every available tape and even calculated several variables by hand,

we still could keep only 59 observations in our sample of bankrupt companies. Most of the companies were "lost" because we could not find ownership data about management purchase and sale of stock or segment information about their lines of business. After determining the composition of the bankruptcy sample, we matched the sample by industry and asset size and selected 63 companies that did not go bankrupt and had the data we needed. Table 12 presents the companies in our original bankrupt and matching samples.

Orthodox logist analysis requires that samples be selected randomly from a population of bankrupt and non-bankrupt companies. In almost all studies on bankruptcy which have used the logist analysis methodology, however, the sample has been selected using non-random, state-based criteria. Therefore, the probability of bankruptcy derived by logist analysis for any firm i is actually the probability in the specific sample, not the general population. The relationship between the probability of bankruptcy based on the population and the probability of bankruptcy based on the sample depends on how the sample of bankrupt companies was selected from the population in general as well as how the sample of non-bankrupt companies was selected. Because of this, the probabilities from logist analysis must be adjusted for the effects of the sample selection, or else they would become meaningless because by selecting a sample differently, we can derive completely different results. In the following

chapter, we explain how we adjusted our results and discuss in greater detail how the selection process actually affects the results of logist analysis.

Table 12. Original (Bankrupt) and Matching Sample for Deriving Empirical Bankruptcy Model

Original Sample

M#	CNUM	Company Name	T_0	Ind DNUM	Asset
1	2073	ATI Inc.	84	237399	12.40
2	13900	Aldebaran Drilling Co. Inc.	87	171381	5.83
3	14419	Aldon Industries Inc.	87	22272	9.48
4	25909	American Fuel Technologies	86	42860	1.20
5	37460	Apache Energy & Minerals	84	246792	5.40
6	40150	Argonaut Energy Corp.	86	171311	15.47
7	77266	Beker Industries	85	42870	267.90
8	124187	Buttes Gas & Oil Co.	87	171311	389.52
9	140556	Capitol Air Inc.	84	154511	34.75
10	141602	Cardis Corp.	87	215013	195.20
11	159620	Chargit Inc.	87	237399	19.00
12	163742	Chemical Investors Inc.	83	32640	20.60
13	202666	Commodore Resources Corp.	82	171311	0.09
14	208106	Conner Corp.	87	182451	71.83
15	221241	Cosmetic Sciences Inc.	86	238091	1.50
16	225015	Crawford Energy Inc.	85	171381	26.95
17	228885	Crutcher Resources Corp.	86	171389	99.80
18	232827	Cytox Corp.	85	215161	1.30
19	234230	Dakota Minerals Inc.	84	171311	4.70
20	236280	Danker Labs Inc.	85	143851	1.90
21	238136	Datatron Inc.	85	215080	7.30
22	254674	Discovery Oil Ltd.	86	171311	15.16
23	278902	Econo Therm Energy Systems	86	93443	22.88
24	292009	Empire Oil & Gas Co.	83	171381	31.34
25	292666	Energy Exchange	85	171311	55.43
26	292935	End-Lase Inc.	86	215080	12.50
27	293799	Enterprise Technologies Inc.	85	215170	33.30
28	364652	Gamex Industries Inc.	82	193990	2.00
29	402274	Gulf Energy Corp.	84	171311	5.05
30	423276	Helionetics Inc.	86	123621	27.90
31	456704	Information Displays Inc.	84	123686	37.00
32	460380	Intl Stretch Prods	84	22200	5.88
33	460468	Intl Teldata Corp.	85	246794	0.65
34	461027	Interstate Motor Freight	84	154210	82.28
35	552813	MGF Oil Corp.	84	171311	342.92
36	559150	Magic Marker Industries Inc.	86	193950	8.10
37	585163	Mego International	82	193944	46.00
38	595215	Mid-America Petroleum Inc.	86	171381	22.47
39	628300	Mutual Oil of America Inc.	86	171311	29.97
40	635080	National Business Comm. Corp.	85	225900	5.55
41	638777	NATPAC Inc.	86	225411	25.90
42	654048	Nicklos Oil & Gas Co.	85	171381	96.78
43	682121	OmniMedical	84	237600	9.00
44	712221	People's Restuarants Inc.	86	225812	41.79
45	747623	Quanta Systems Corp.	85	113664	2.40

Table 12--continued.

46	748379	QuikPrint of America Inc.	83	246794	2.30
47	761049	Reser's Fine Foods Inc.	86	12013	9.70
48	765361	Richmond Tank Car Co.	83	133743	101.30
49	771044	Roblin Industries	85	93312	32.13
50	795872	Sambo's Restaurants	81	225812	220.94
51	802828	Santec Corp.	85	123688	2.90
52	805567	Saxon Industries	82	32600	486.60
53	816068	Seiscom Delta, Inc.	86	171382	23.36
54	817910	Servamatic Systems Inc.	86	175900	26.36
55	925523	Viable Resources Inc.	84	171311	6.25
56	929073	Vuebotics Corp.	84	237391	2.10
57	984010	Xenerex Corp.	85	171311	30.95
58	984126	Xonics Inc.	84	143861	15.40
59	989875	Zytrex Corp.	84	113674	6.50

Matching Sample

M#	CNUM	Company Name	T_0	Ind DNUM	Asset
1	204682	Comptek Research Inc.	84	237372	12.44
2	866055	Summit Energy Inc.	85	171311	28.80
3	550819	Lydall Inc.	87	22200	50.14
4	524038	Lee Pharmaceuticals	86	42844	6.50
5	255264	Diversified Industries Inc.	84	246200	68.23
6	870738	Swift Energy Co.	86	171311	12.60
7	628850	NCH Corp.	85	42842	272.10
8	136420	Canadian Occidental Petroleum	87	171311	317.94
9	443784	Hudson General Corp.	84	154580	48.30
10	480827	Jorgensen (Earle M.) Co.	87	215051	197.11
11	205477	Computer Task Group Inc.	87	237372	29.92
12	878504	Technical Tape Inc.	83	32640	31.00
13	69689	Baruch-Foster Corp.	82	171311	18.10
14	674098	Oakwood Homes	87	182451	56.00
15	872625	TRC Cos Inc.	86	238911	3.04
16	209705	Consolidated Oil & Gas	85	171311	123.23
17	786629	Sage Energy Co.	86	171311	139.40
18	847660	Speed-O-Print Business Machines	85	215081	7.65
19	192108	Coeur D'Alene Mines Corp.	84	171040	22.58
20	914802	University Patents Inc.	85	143851	18.18
21	239133	Davis Water & Waste	85	215051	36.48
22	971889	Wilshire Oil of Texas	86	171311	64.04
23	208258	Conquest Exploration Co.	86	9480	17.19
24	739647	Prairie Oil Royalties Co. Ltd.	83	171311	32.75
25	666416	Northgate Exploration Ltd.	85	171040	117.60
26	46357	Astrex Inc.	86	215065	25.30
27	6351	Adams Resources & Energy Inc.	85	215172	35.58
28	250568	DesignCraft Industries	82	193911	7.62
29	131069	Callahan Mining Corp.	84	171040	55.97
30	458683	InterGraph Corp.	86	123686	28.90
31	369032	General Automation	84	123681	38.60

Table 12-continued.

32	732852	Pope, Evans & Robbins Inc.	84	22330	4.89
33	647072	New Mexico & Arizona Land	85	246519	36.49
34	893552	Transcon Inc.-California	84	154213	79.30
35	960878	Westmoreland Coal Co.	84	171211	376.30
36	55716	BSN Corp.	86	193949	22.24
37	43147	Artra Group Inc.	82	193960	51.91
38	553748	MSR Explorations Ltd.	86	171311	26.90
39	655555	Nord Resources Corp.	86	171090	66.10
40	204909	Computer Factory Inc.	85	225995	13.88
41	885539	Three D Department	86	225700	21.15
42	379355	Global Natural Resources Inc.	85	171311	105.80
43	29429	American Science Engineering	84	237391	13.97
44	362232	G R I Corp	86	225961	49.34
45	362360	GTI Corp	85	113679	13.05
46	170819	Christiana Companies	83	246552	44.48
47	208093	Connelly Containers Inc.	86	12030	18.50
48	879369	TeleFlex Inc.	83	133714	109.30
49	707389	Penn Engineering & Mfg Corp.	85	93452	39.01
50	476502	Jerrico Inc.	81	225812	238.50
51	238085	Datametrics Corp.	85	123688	3.80
52	313693	Federal Paper Board Co.	82	32631	472.83
53	212576	Convest Energy Partners	86	171311	34.49
54	658136	North Canadian Oils Ltd.	86	171311	182.00
55	427879	Hershey Oil Corp.	84	171311	30.38
56	27258	American List Corp.	84	237331	2.39
57	208285	Conquest Exploration Co.	84	171311	123.16
58	942622	Watsco Inc.	84	143822	19.97
59	590262	Merrimac Industries Inc.	84	113663	9.34

"M#" is the matching number, which is used to match the observations in the bankrupt and matching samples. "CNUM" and "DNUM" are the company and industry classifications. "T_0" is the year during which the company filed for Chapter 11 for companies in the bankrupt sample, or the last year data was collected for our research for companies in the matching sample. "Ind." is the industry code according to our definitions. "Asset" is the company's asset size.

CHAPTER 7
RESULTS OF EMPIRICAL MODELS OF BANKRUPTCY

Using the sample data described in Chapter 6, we were able to derive five probabilistic models, designated P_1 through P_5. All of them are based on the factors described in Chapter 5, and they assess bankruptcy risk one through five years ahead of time corresponding to the subscripton P_n. The only difference among these distinct models is in their coefficients: they all assume the form discussed in Chapter 5. Table 13 shows the signs of the coefficients of the variables for each model P_n.

Most of these coefficients conform to our expectations as explained in Chapter 5, but others show significant differences. The signs for the coefficients of the balance ratio and the net rate of management stock acquisitions seem to vary randomly but lean towards being positive, while we expected both to be negative. Both of these variables can be positive or negative, and our expectation was stated for the "normal" case for which the expected value of the variable is positive. Looking at the raw data, a significant number of the values in both samples were negative, so we would have to

reverse the coefficient sign convention. Hence, the positive signs give the expected signal and it is only our view of "normal" values for the variables that could not be verified empirically. We suspect that this result can be explained in large part by the way the matching sample was constructed. The match was made by industry and asset size, and it is evident that many of the pairs came from "troubled" industries. It is an empirical question, but we suspect that a random sample from all industries would conform to the original expectations.

The other sign anomalies are not as troubling. The first four variables (Group I) are expected to be most significant close to bankruptcy, and three of the four have the correct signs in the first three years. Also, the last four variables (Group II) are expected to be most significant in earlier years, and three of the four have the correct sign in the last four years. We believe that this pattern confirms the validity of our expectations.

Logist analysis provides a technique that allows us to find the most significant variables in any predictive model. A variable is "most significant" if, by Chi-Square Q-statistic and MLE's statistic, they meet the requirements of entry and stay significance levels pre-specified for the model. Our entry and stay significance levels were set at 0.05. Table 14 shows the most significant variables in each of our models. Capital intensity is significant in all periods. This means

that the nature of a company's line of business always plays a significant role. When bankruptcy is far into the future, our data indicate that this factor plays the largest role of the eight variables used in our model. As we approach bankruptcy, especially one year ahead of bankruptcy, however, ROA, FCC, and Market/Book Ratio become increasingly significant. This confirms our view that in the short-term, variables in the company operating and profitability indicators group that are weighted toward a company's current financial data would play significant roles. Other factors, such as relative sales growth, balance ratio of income and sales growth, and management stock acquisition, have also played increasingly larger roles near the time of bankruptcy.

To investigate this timing phenomenon further, we built and tested separate predictive models based on the groups defined in Chapter 5. Group I was composed of company operating and financial indicators and included ROA, market-to-book ratio, FCC, and balance ratio. Group II was composed of fundamental company characteristics indicators and included the net rate of management stock acquisitions, the relative sales growth rate, the relatedness ratio, and capital intensity. We then compared the predictive power and effectiveness of the main models built with all eight variables with those of the Group I and Group II models. Table 15 shows the predictive powers and effectiveness of all three sets of models. Figure 4 shows the predictive power of

our main model, and Figure 5 compares the Group I and Group II models.

We then investigated into the classification powers of our model by examining the empirical probability density functions for bankrupt and non-bankrupt firms. We divided the range of probability of bankrupt from 0 to 1.0 into ten equal intervals. The percentage of bankrupt and non-bankrupt firms relative to the total number of firms that they present which fall within each of these intervals for the five different time periods t_1 through t_5 are tabulated and shown in Tables 16 and 17. The percentages are plotted against the mid-value of the interval to obtain the discrete approximation of the distributions of the bankrupt and non-bankrupt probabilities in Figures 6 to 15. The probabilities of the two groups are shown to diverge significantly by their respective bar graphs. The bankrupt group is clearly skewed toward the higher probabilities of failure that our model derived, while the non-bankrupt group is clearly skewed toward the lower probabilities of failure. These results are similar to those of Zavgren (1985). Her paper, however, only presented original probabilities, while we present both the original probabilities and those probabilities adjusted for sample selection (as discussed below).

As mentioned in the previous chapter, because we selected our data with non-random, state-based criteria, we must adjust the probabilities derived from logist analysis.

For any given firm i in the general population with a probability P of bankruptcy, logist analysis would give a probability P' of bankruptcy for that company in our specific sample. We must find ways of finding a relationship between P and P' and also between the structures of our samples. Assuming that there are N_1 bankrupt and N_2 non-bankrupt firms in the general population and n_1 bankrupt and n_2 non-bankrupt firms in our bankrupt and non-bankrupt samples, P', according to Bayes' formula for conditional probability, is equal to:

$$P' = P * (n_1/N_1) / \{P * (n_1/N_1) + (1-P) * (n_2/N_2)\} \quad (1)$$

Previous work, such as Palepu (1986), which tried to predict merger targets using logist analysis models, have partially explored this relationship, but he only gave a formula for P' in the special case when $n_1=N_1$. We, however, derived a general formula for P' for cases when n_1 is not equal to N_1, and n_2 is not equal to N_2:

Let $\alpha_1 = n_1/N_1$,
$\alpha_2 = n_2/N_2$,

Then formula (1) can rewritten as

$$P' = (\alpha_1 * P)/\{(\alpha_1 * P) + (1-P) * \alpha_2)\} \quad (2)$$

Substituting $P = (1 + \exp\{-Y_j\})^{-1}$ into (2), we derive the formula for any value of α_1 and α_2:

$$P' = (1 + \exp\{lg(\alpha_2/\alpha_1) - Y_j\})^{-1}. \quad (3)$$

This formula implies the following relationships between the samples and P' and P:

If $\alpha_1 = \alpha_2$:
P' = P, Type I error will not change,
Type II error will not change.

If $\alpha_1 > \alpha_2$:
$P' > P$, Type I error will increase,
Type II error will decrease.

If $\alpha_1 < \alpha_2$,
$P' < P$, Type I error will decrease,
Type II error will increase.

According to this formula, without adjustments, we can derive a model with an artificially high or artificially low type I error by settling for an artificially low or artificially high type II error, or vice versa, simply by selecting the right samples. After adjustments, artificial type I and II errors are still possible because, even then, α_1 and α_2 are part of the model. Therefore, to have meaningful probability models with the logist analysis methodology, we must always first adjust for α_1 and α_2 and then report their values along with our type I and type II errors. Table 18 presents such data for our sample.

Since $\alpha_1 > \alpha_2$ in our samples, type I error increased after adjustments were made, while type II error decreased. We can observe this same phenomenon by comparing Figures 6 through 10 with Figures 11 through 12, respectively.

Our data lead to some interesting conclusions. First, we have succeeded in building a model whose predictive power does not fall precipitously as time before bankruptcy increases. Whereas Altman's ZETA model, under optimal conditions, is 96% accurate one year before bankruptcy but only 60% accurate five years before bankruptcy, our model's

predictive power, based on data from one experimental sample, is relative stable. It is most effective one year before bankruptcy, with 96.0% accuracy (as measured by the C-Index of logist analysis), but even at its lowest point, three years before bankruptcy, it still has 89.0% accuracy, and five years before bankruptcy it is 95.1% accurate.

Second, we have found that during different periods before bankruptcy, different groups of variables become important in predicting bankruptcy. When close to bankruptcy, the Group I financial variables have very high predictive power. As we move farther back in time and try to predict bankruptcy farther ahead of time, we found that these variables' predictive powers started to wane. The Group II fundamental variables became increasingly more powerful as we moved farther back in time. This demonstrates that there is a time relationship between our fundamental variables and the future financial position of the company.

Table 13. Signs of Coefficients

Model	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8
P_1	-	-	-	-	+	+	+	-
P_2	-	-	+	-	-	+	-	-
P_3	-	-	+	-	-	+	-	-
P_4	-	-	+	+	-	-	-	-
P_5	+	-	-	-	-	-	-	-

P_1 through P_5 are models for predicting bankruptcy one to five years ahead of time.

b_1 through b_8 are coefficients of the following variables:

b_1: ROA (EBIT/TA)
b_2: FCC
b_3: Balance Ratio
b_4: Market/Book Ratio
b_5: Relatedness Ratio
b_6: Net Rate of Management Stock Acquisitions
b_7: Relative Sales Growth Rate
b_8: Capital Intensity.

Table 14. Most Significant Variables in Forecasting Bankruptcy

Model	Most Significant Variables
P_1	ROA, FCC, Balance Ratio, Capital Intensity, Market/Book Ratio
P_2	Relative Sales Growth, FCC, Capital Intensity
P_3	ROA, Net Rate of Management Stock Acquisitions, Relative Sales Growth, Capital Intensity
P_4	Capital Intensity
P_5	Capital Intensity

P_1 through P_5 are models for forecasting bankruptcy one through five years ahead of time, respectively.

Table 15. Predictive Power and Effectiveness of Different Models

Years:	1	2	3	4	5
Eight-Variable Models:					
C-Index:	0.960	0.957	0.892	0.909	0.951
X^2	59.75	69.31	48.48	44.51	45.94
(SL with 8 DF)	0.50%	0.50%	0.50%	0.50%	0.50%
L.H. Ratio Index	0.5969	0.6133	0.4135	0.4819	0.5980
Group I Models:					
C-Index:	0.929	0.873	0.771	0.740	0.598
X^2	49.63	39.88	16.33	10.33	3.83
(SL with 4 DF)	0.50%	0.50%	0.50%	5.00%	50.00%
L.H. Ratio Index	0.4958	0.3529	0.1365	0.1074	0.0460
Group II Models:					
C-Index:	0.819	0.770	0.835	0.863	0.889
X^2	16.45	27.43	35.19	35.31	32.47
(SL with 4 DF)	0.50%	0.50%	0.50%	0.50%	0.50%
L.H. Ratio Index	0.1643	0.2427	0.3001	0.3823	0.4227

The C-Index comes from logist analysis and indicates the classification accuracy of the model. X^2 (or Chi-Square) is the -2 log likelihood ratio chi-square statistic of the model.

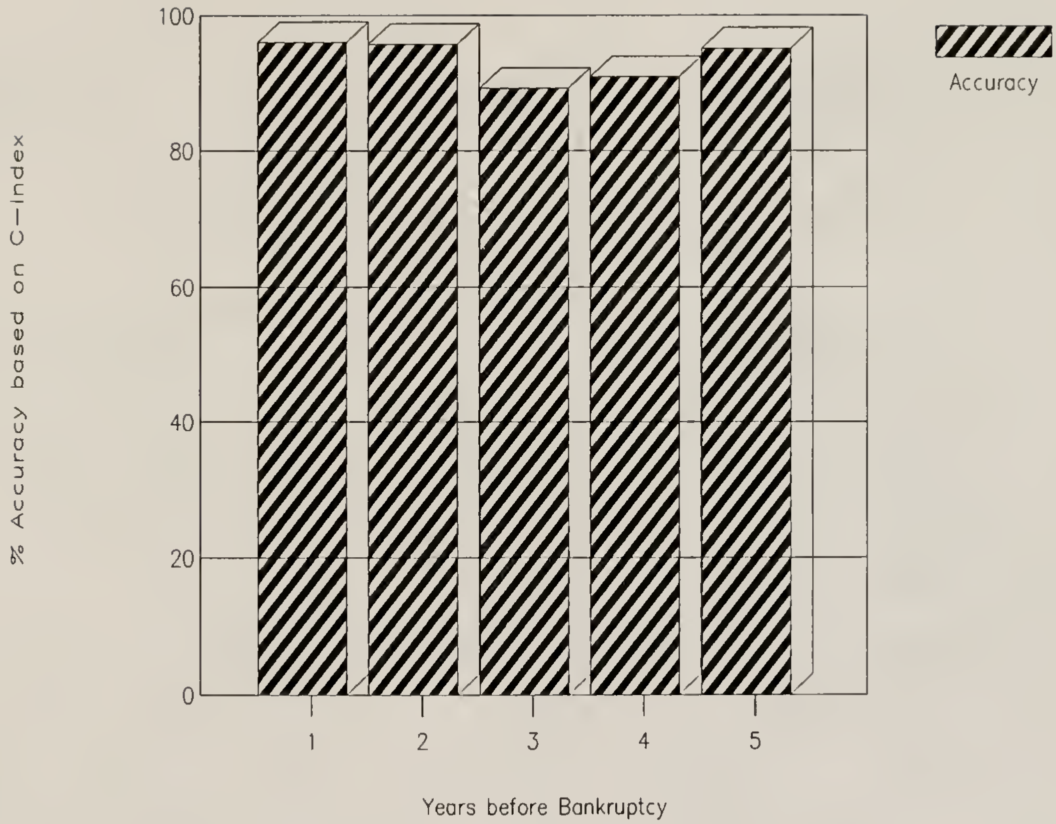


Figure 4. Classification Accuracy of Empirical Model of Bankruptcy

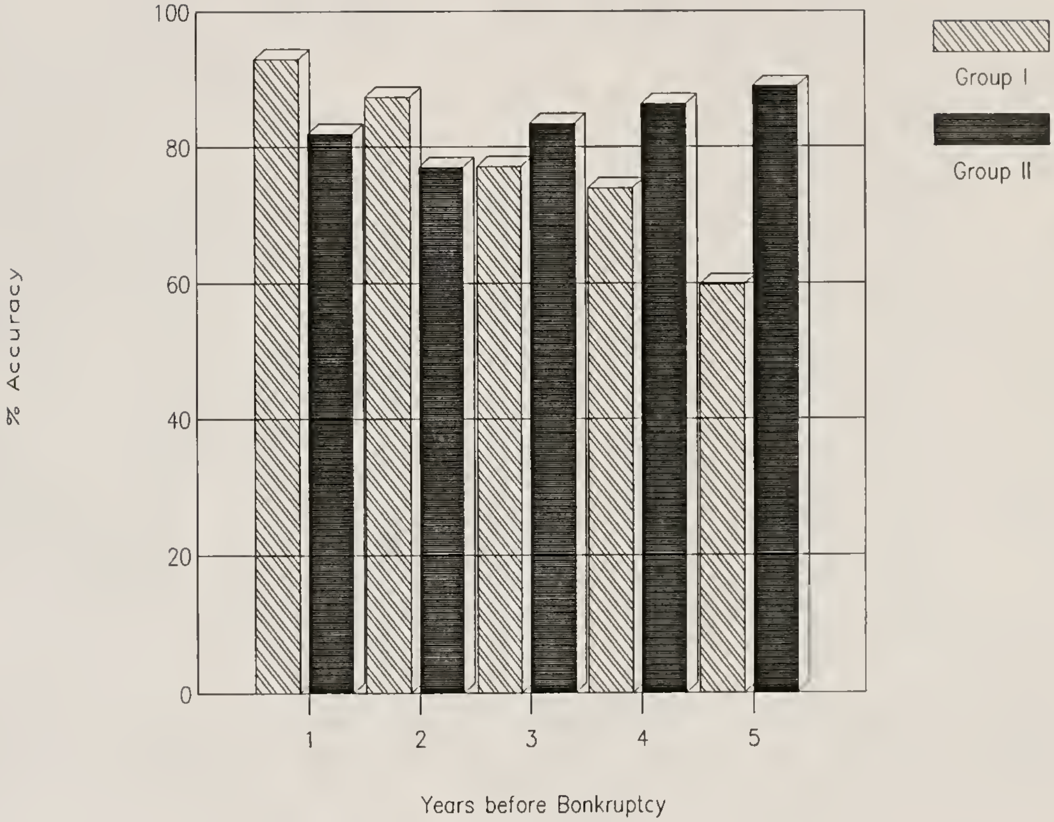


Figure 5. Classification Accuracy of Models Based on Group I and Group II Variables

Table 17. Empirical Probability Density Function of Unadjusted Bankrupt Probabilities

Time 1

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	66.04%	22.64%	1.89%	1.89%	1.89%	0.00%	0.00%	3.77%	1.89%	0.00%
Bankrupt	3.85%	3.85%	3.85%	3.85%	7.69%	7.69%	0.00%	7.69%	11.54%	50.00%

Time 2

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	66.67%	12.50%	8.33%	0.00%	0.00%	2.08%	2.08%	2.08%	4.17%	2.08%
Bankrupt	0.00%	0.00%	5.71%	0.00%	14.29%	0.00%	8.57%	8.57%	8.57%	54.29%

Time 3

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	45.65%	4.35%	8.70%	13.04%	6.52%	6.52%	10.87%	2.17%	2.17%	0.00%
Bankrupt	2.56%	0.00%	2.56%	5.13%	10.26%	12.82%	5.13%	28.21%	5.13%	28.21%

Time 4

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	52.38%	7.14%	16.67%	4.76%	2.38%	2.38%	11.90%	2.38%	0.00%	0.00%
Bankrupt	0.00%	3.70%	3.70%	14.81%	0.00%	14.81%	11.11%	7.41%	3.70%	40.74%

Time 5

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	73.68%	5.26%	5.26%	2.63%	0.00%	2.63%	2.63%	5.26%	2.63%	0.00%
Bankrupt	0.00%	4.76%	0.00%	4.76%	9.52%	4.76%	9.52%	9.52%	23.81%	33.33%

"Mid-value" is the mid-value of the probability intervals. "Non-bkpt" and "Bankrupt" are the percent of non-bankrupt and bankrupt observations which fell within that interval.

Table 18. Empirical Probability Density Function of Adjusted Bankrupt Probabilities

Time 1

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	39.62%	15.09%	11.32%	9.43%	13.21%	0.00%	3.77%	1.89%	0.00%	5.66%
Bankrupt	0.00%	0.00%	3.85%	0.00%	3.85%	3.85%	3.85%	7.69%	7.69%	69.23%

Time 2

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	43.75%	8.33%	2.08%	12.50%	4.17%	8.33%	8.33%	0.00%	2.08%	10.42%
Bankrupt	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.71%	0.00%	17.14%	77.14%

Time 3

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	32.61%	8.70%	0.00%	2.17%	4.35%	2.17%	4.35%	10.87%	19.57%	15.22%
Bankrupt	0.00%	0.00%	0.00%	2.56%	0.00%	0.00%	2.56%	5.13%	20.51%	69.23%

Time 4

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	38.10%	7.14%	4.76%	4.76%	4.76%	9.52%	9.52%	2.38%	9.52%	9.52%
Bankrupt	0.00%	0.00%	0.00%	0.00%	3.70%	0.00%	3.70%	14.81%	22.22%	55.56%

Time 5

Mid-value	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Non-bkpt	57.89%	7.89%	5.26%	2.63%	5.26%	2.63%	2.63%	2.63%	5.26%	7.89%
Bankrupt	0.00%	0.00%	0.00%	4.76%	0.00%	0.00%	0.00%	14.29%	9.52%	71.43%

"Mid-value" is the mid-value of the probability intervals. "Non-bkpt" and "Bankrupt" are the percent of non-bankrupt and bankrupt observations which fell within that interval.

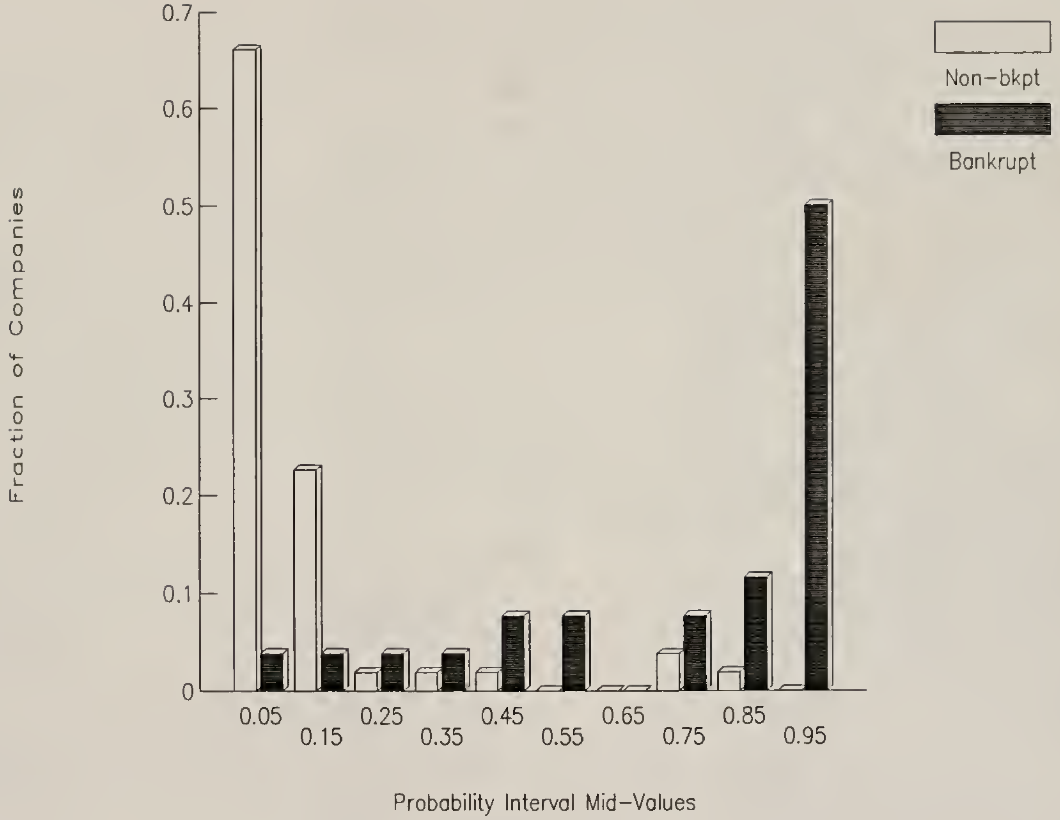


Figure 6. Unadjusted Empirical Probability Density Function, 1 Year Before Bankruptcy

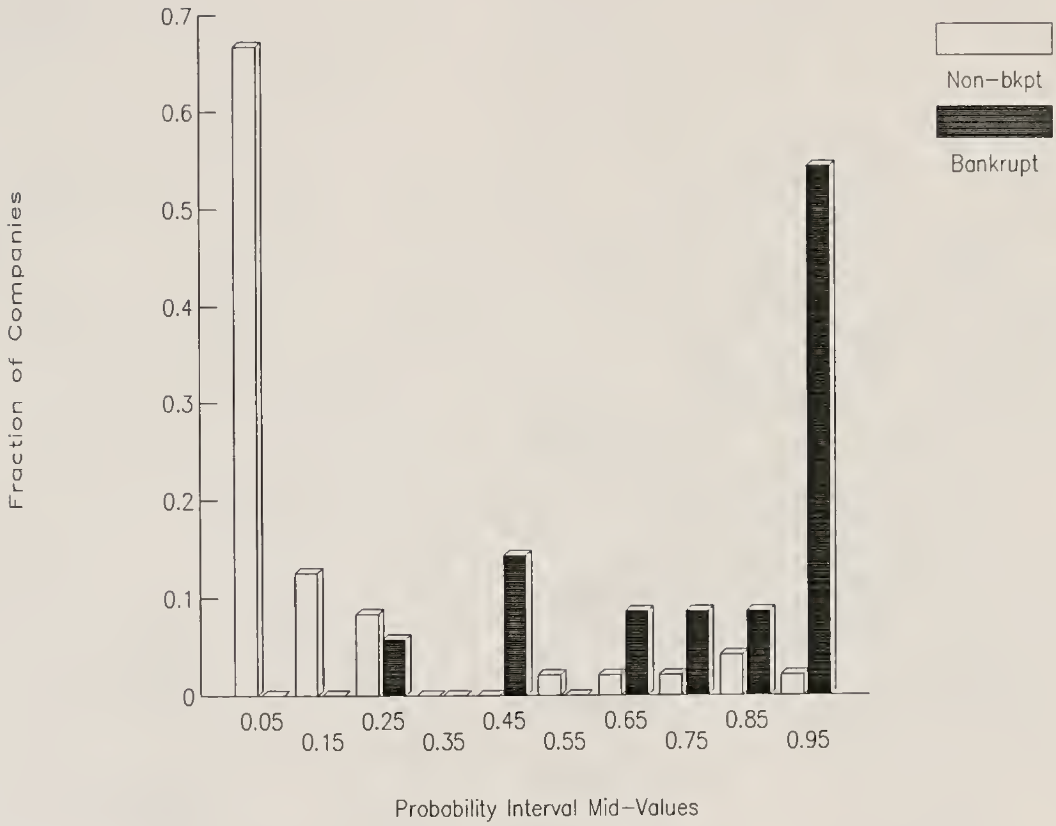


Figure 7. Unadjusted Empirical Probability Density Function, 2 Years Before Bankruptcy

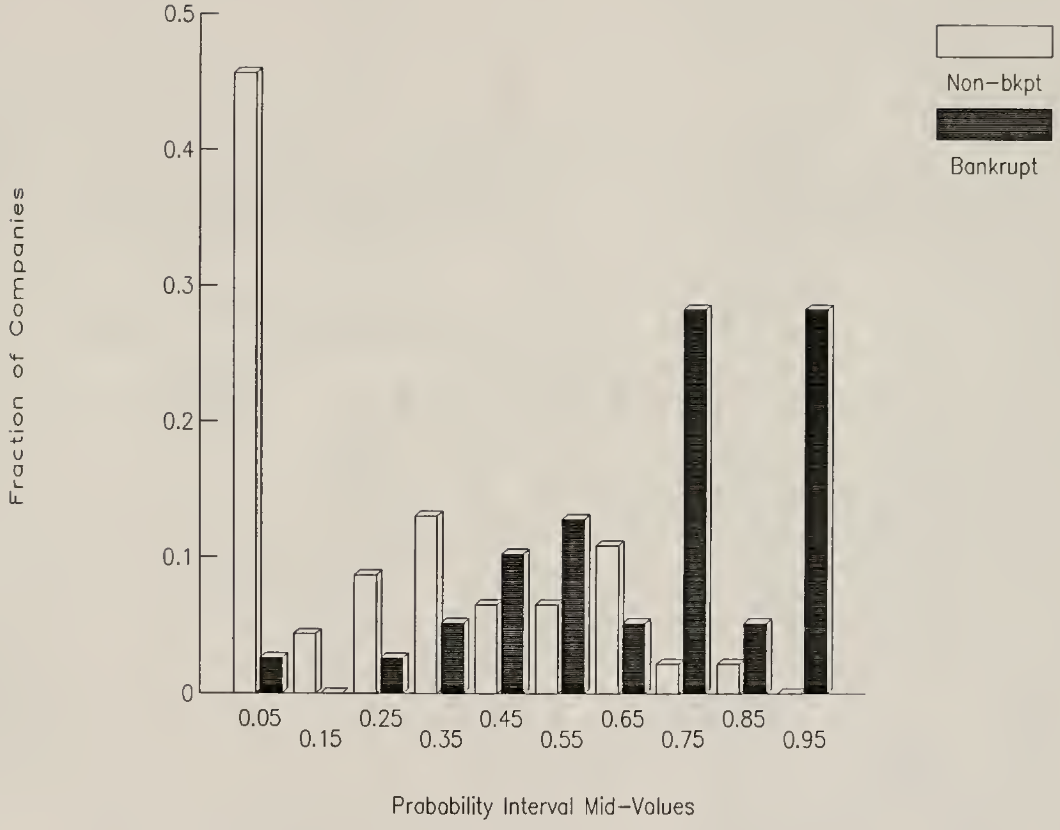


Figure 8. Unadjusted Empirical Probability Density Function, 3 Years Before Bankruptcy

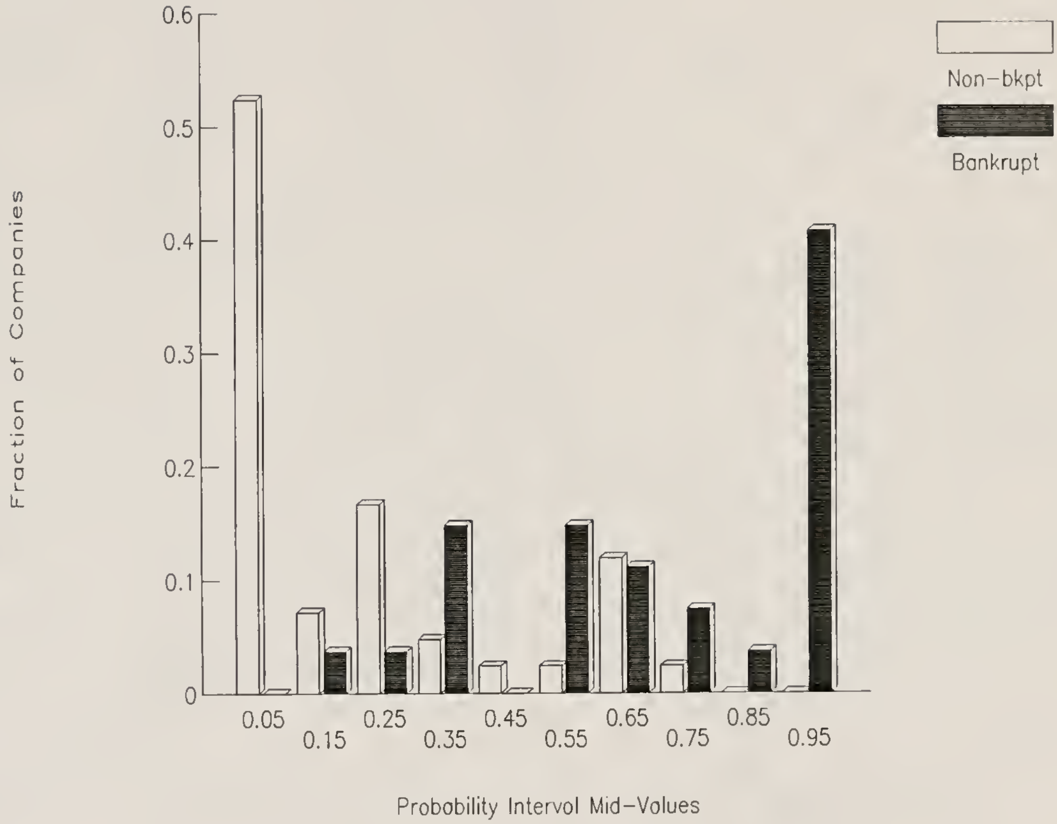


Figure 9. Unadjusted Empirical Probability Density Function, 4 Years Before Bankruptcy

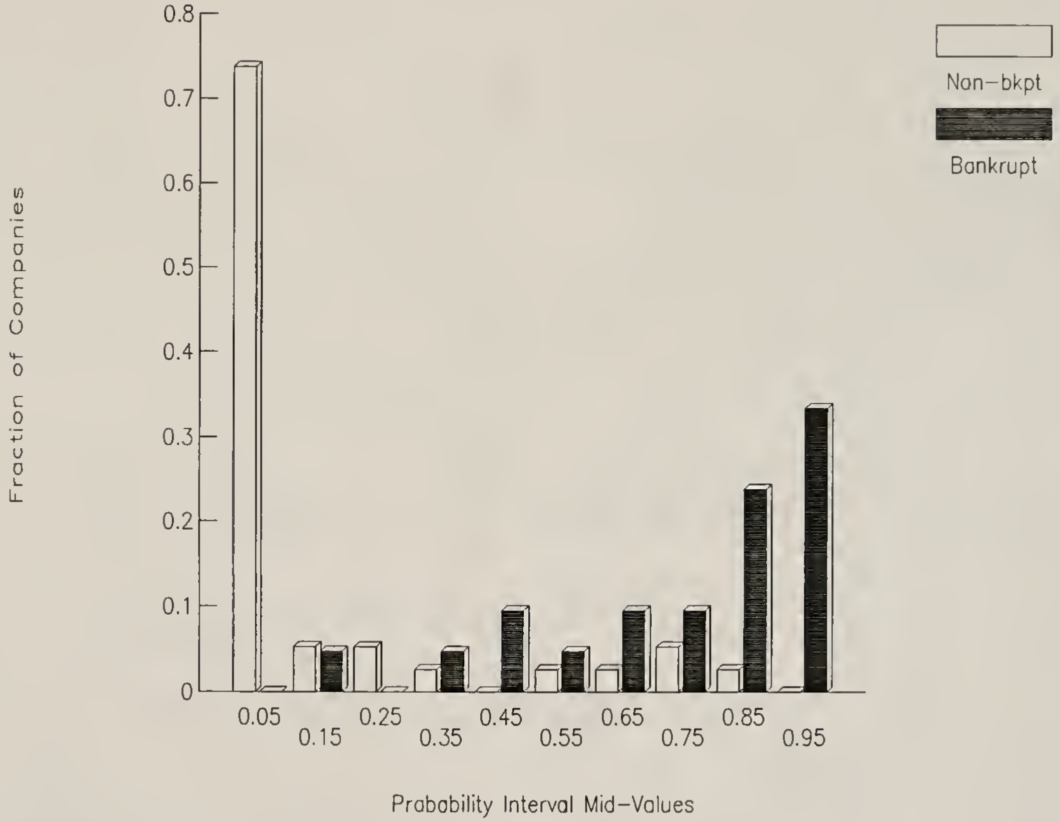


Figure 10. Unadjusted Empirical Probability Density Function, 5 Years Before Bankruptcy

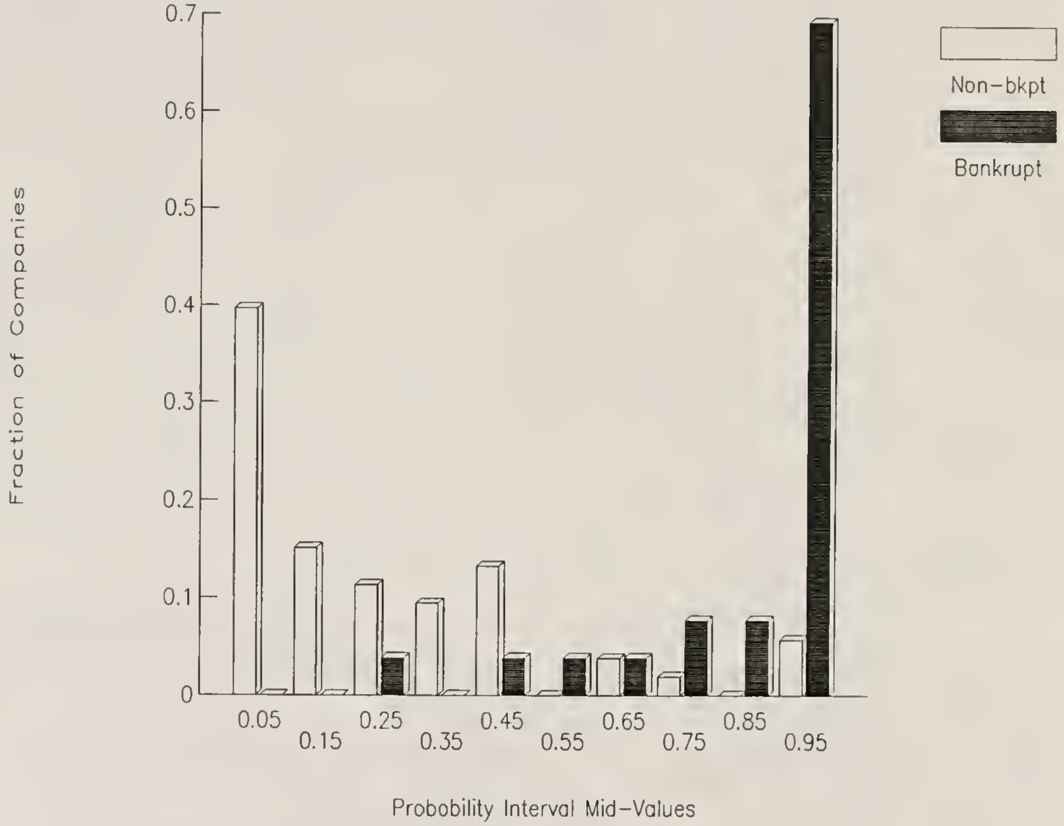


Figure 11. Adjusted Empirical Probability Density Function, 1 Year Before Bankruptcy

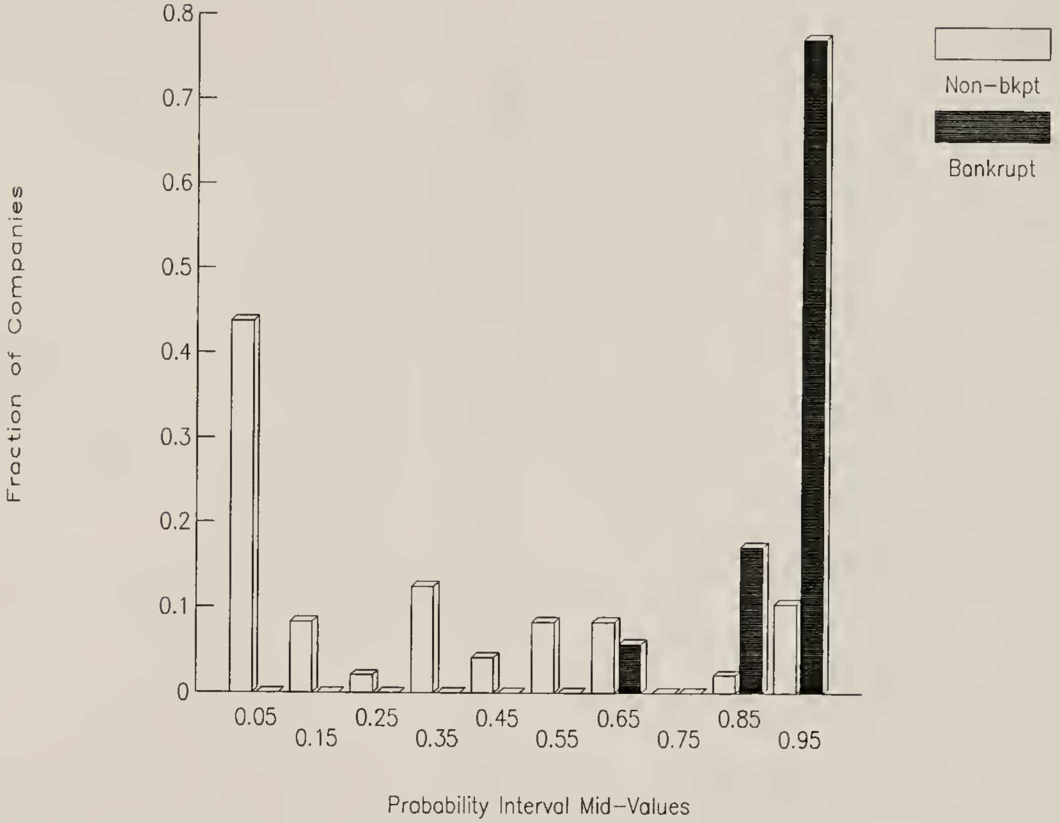


Figure 12. Adjusted Empirical Probability Density Function, 2 Years Before Bankruptcy

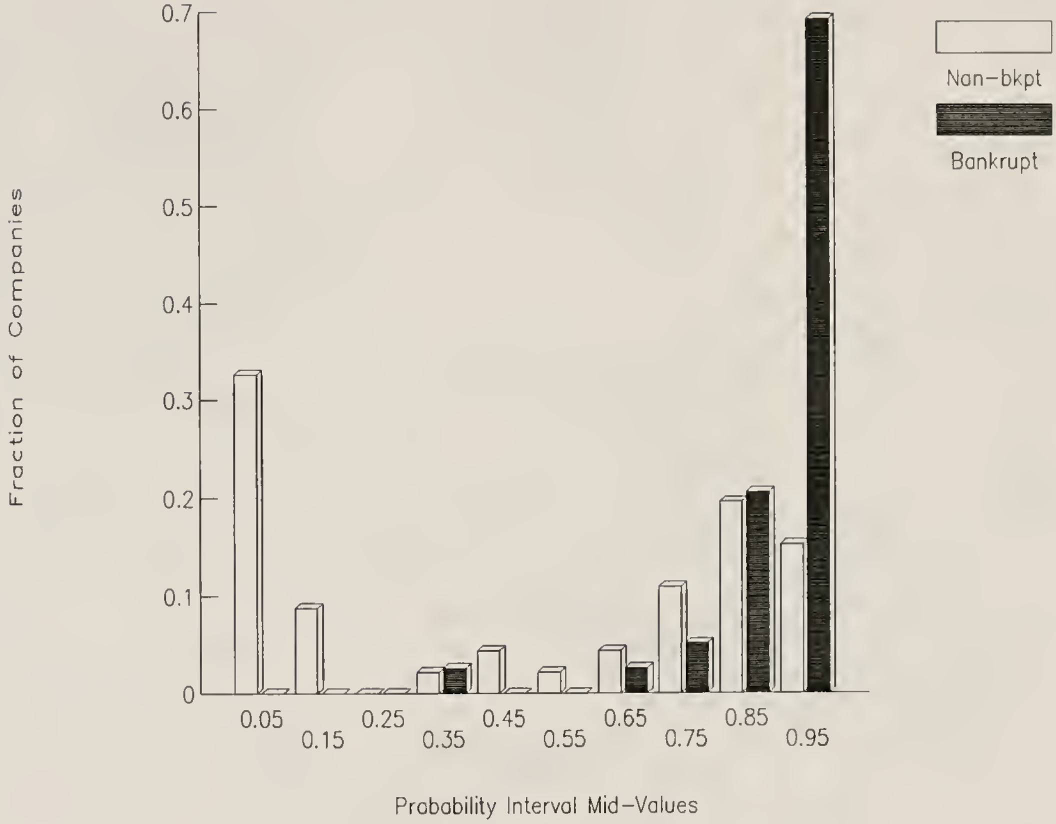


Figure 13. Adjusted Empirical Probability Density Function, 3 Years Before Bankruptcy

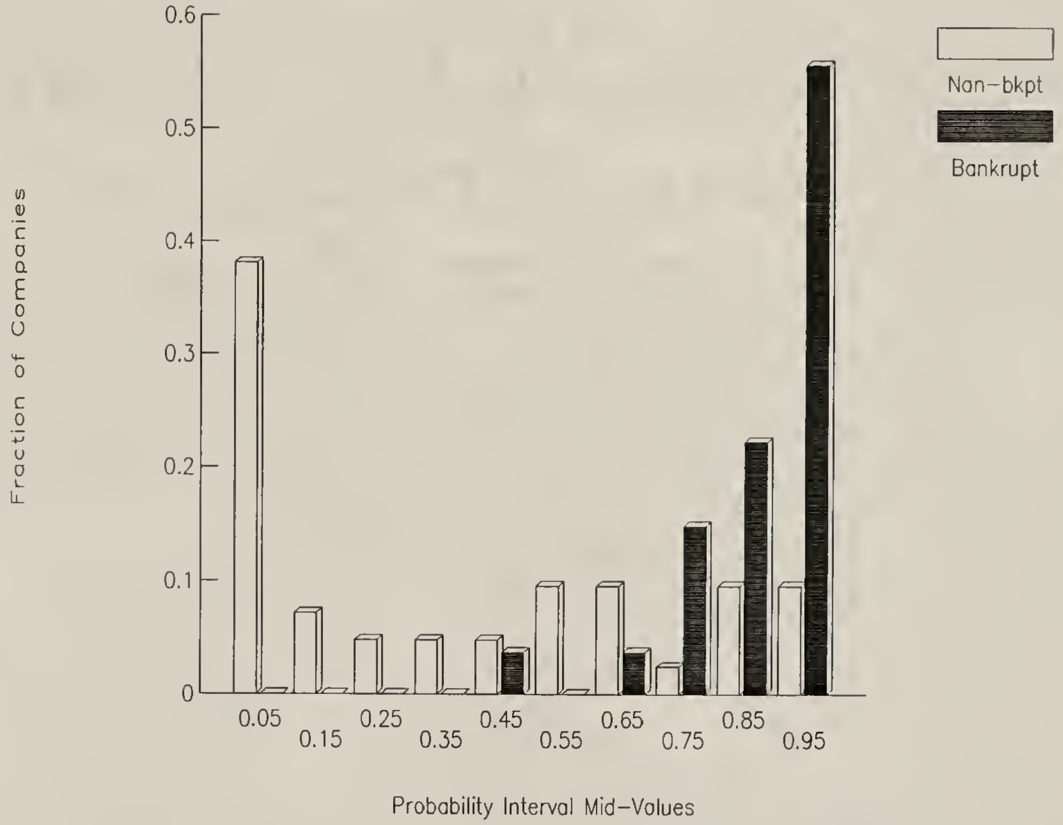


Figure 14. Adjusted Empirical Probability Density Function, 4 Years Before Bankruptcy

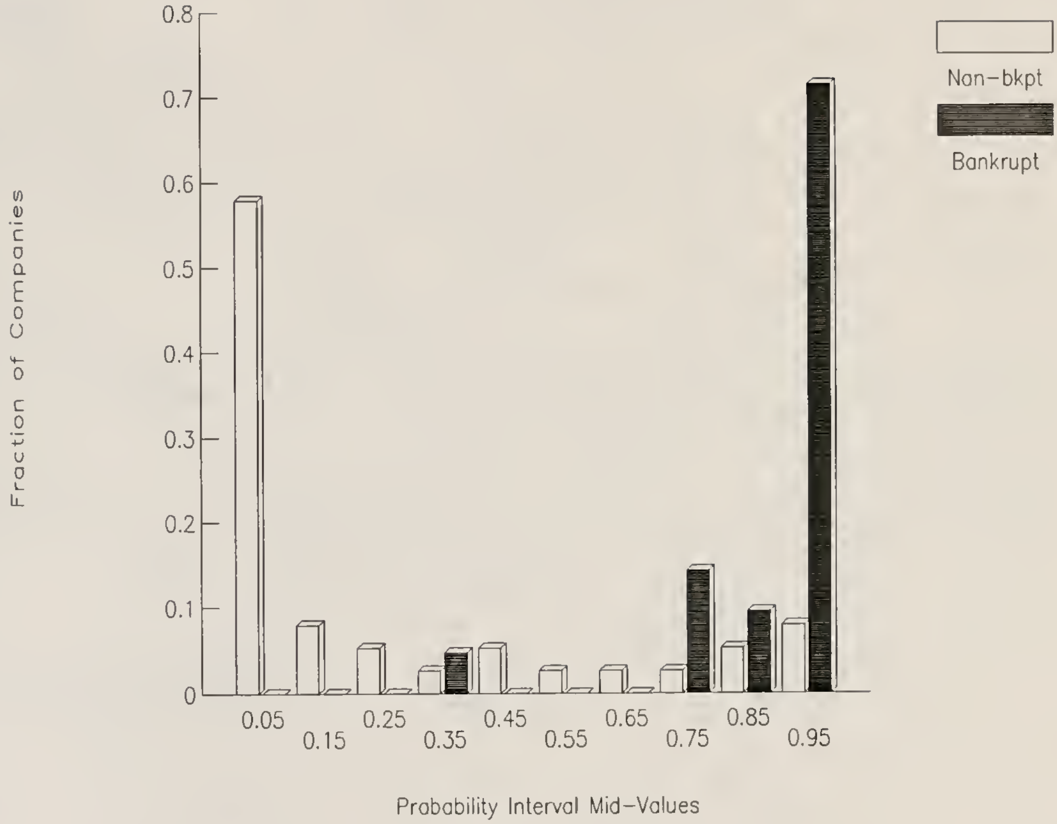


Figure 15. Adjusted Empirical Probability Density Function, 5 Years Before Bankruptcy

Table 16. Adjusted and Unadjusted Correct Ratio, Type I Error, and Type II Error for our Sample

Unadjusted

	T_1	T_2	T_3	T_4	T_5
Correct Ratio	88.6%	84.3%	78.8%	81.2%	84.7%
Type I Error	13.0%	17.7%	24.4%	25.0%	22.7%
Type II Error	10.7%	14.3%	18.2%	14.6%	10.8%

Adjusted

	T_1	T_2	T_3	T_4	T_5
n_1	26	35	39	27	21
n_2	53	48	46	42	38
α_1 (N_1 =315)	0.0825	0.1111	0.1238	0.0857	0.0667
α_2 (N_2 =2460)	0.0215	0.0195	0.0187	0.0171	0.0154
Correct Ratio	89.87%	83.13%	70.59%	76.81%	84.75%
Type I Error	20.0%	28.57%	38.71%	37.21%	28.57%
Type II Error	4.08%	0.00%	4.35%	0.00%	3.23%

CHAPTER 8
SUMMARY AND CONCLUSIONS

Research Summary

In this dissertation, we explore two areas that present day bankruptcy research has not fully addressed. First, we look at the relationship between financial markets and bankruptcy. We examine the risk premia trend of corporate bonds as companies neared bankruptcy. Then, we studied how bond downgrades, which, in principle, should provide new information to the market about risks of default and bankruptcy, impacted the markets, as measured by the disturbance on a company's daily stock rate of return.

Second, we built a model of bankruptcy which assesses bankruptcy risk based not only on financial data but also on more fundamental characteristics of a company. This model incorporates new dimensions into bankruptcy research that have, to date, been left out.

In the area of financial markets and bankruptcy, our research reached two major conclusions. First, we found that the market can adequately assess the risk of bankruptcy in its

overall assessment of risk. Our data showed how, as companies moved towards filing for Chapter 11, the market successively increased the risk premium on their bonds, thus demonstrating that the market appreciated the increasing risk of bankruptcy and accounted for it in its valuation of securities.

Second, we showed that a bond rating downgrade has a notable impact on the market, as measured by the daily rates of return of a company's stock. When a company's bond is downgraded, its stock's daily rates of return tend to fall precipitously. This indicates that bond downgrades provide new information to the market, which then uses it to evaluate the company's risk. Although some past research studies has not reached the same conclusion, we believe that our research has contributed significantly to this area of research because it is unique--this is the first research study to incorporate both the event study methodology and daily rates of return on a company's stock.

Furthermore, our conclusion about bond downgrades is also significant in a different way. While past research has argued back and forth about a "lag" phenomenon, whether the market anticipates or reacts to a bond downgrade, in our research we considered such a lag phenomenon to be merely short-term and therefore not meaningful. That is, we think of a "lagging" bond downgrade which followed a rise in the risk premium as the leading bond downgrade to another rise in the risk premium. Hence, there is really no sense in talking

about a lead or lag phenomenon. Rather, it is more important to consider the long-term effects of a bond downgrade, which are financial distress and perhaps eventual bankruptcy. Our research has shown how bond downgrades actually do provide the market with new information on financial distress and bankruptcy. Therefore, regardless of whether there is a lag or not between a rise in a risk premium and a bond downgrade, bond ratings and downgrades are significant to the market's supply of information and assessment of risk.

In the area of empirical bankruptcy research, we have successfully developed a new empirical model of bankruptcy based on eight variables: return on assets, fixed charge coverage, Balance Ratio, Market/Book Ratio, Relatedness Ratio, Net Rate of Management Stock Acquisitions, Relative Sales Growth Rate, and Capital Intensity. Our results have several interesting implications. First, we found that larger ROA, FCC, market/book ratio, relatedness ratio, relative sales growth, and capital intensity, generally lead to lower chances of bankruptcy. The same also appears to be true for balance ratio and net rate of management stock acquisitions. Second, our research shows that while variables that measure current financial position (our Group I variables) are effective at predicting bankruptcy, their predictive power decreases as we look farther ahead of time. Thus, models based on such variables, such as Altman's ZETA model, will inevitably lose predictive power as one tries to look farther ahead of time.

Meanwhile, however, variables that assess a company's more fundamental characteristics (our Group II variables) have increasing predictive power as we try to look farther into the future. Hence, by combining both types of variables into the same model, we have built a reasonably accurate model whose predictive power does not deteriorate over time. Finally, we have found that, generally, capital intensity, relative sales growth, FCC, and ROA are significant factors in bankruptcy prediction, regardless of the time period.

Our work on this topic makes several novel contributions. First, as stated above, we have built a model whose predictive power is relatively stable. Second, we have established how certain variables can predict bankruptcy in the long-term, which means that they can complement the profitability and financial measures that we currently use to predict bankruptcy in the short-term. Finally, on the subject of logist analysis, we have derived a new formula which describes how sample selection affects the probabilities of the derived model.

Future Research

Both areas that we addressed deserve further attention in future research. First, in the area of financial markets and bankruptcy, considerably more work could be done along the lines of this study. For example, in our dissertation we used the common stock's daily rates of return to determine the

disturbance caused by a bond downgrade. Past researchers, however, have used other measures, such as yield-to-maturity, stock price, and bond price, and they all seem justifiable. Therefore, it would seem logical to try several such measures and to determine which ones yield the most clear and significant results.

Second, in the area of empirical bankruptcy models, much work still remains. First, there is no reason why our list of fundamental company characteristics is exhaustive, and more models can and certainly should be built to take into account other factors about a company's fundamental characteristics into account. Our work was meant to show that such models can be built and they would be more successful at predicting the dangers of bankruptcy than existing models. It is hoped that further work will lead to the development and refinement of models along our lines of thought.

Finally, we believe that there should be further research into the methodology of logist analysis, which is very promising but still somewhat untried. For example, in the area of sample selection, our dissertation has shown how much influence a non-random, state-based sample selection would have on the final models derived. We believe that research into this area is still in its early stages, and further work should certainly be done on the logist analysis methodology.

APPENDIX
RISK PREMIA CURVES

In the following pages, fifty curves are presented. These curves show the risk premia trends of corporate bonds in the sample of 50 companies that we used to study the relationship between risk premium and bankruptcy. A solid line on a curve indicates a rating change by Standard & Poor's, a dotted line one by Moody's. Unless otherwise indicated by an arrow pointing upward, all rating changes are downward changes.

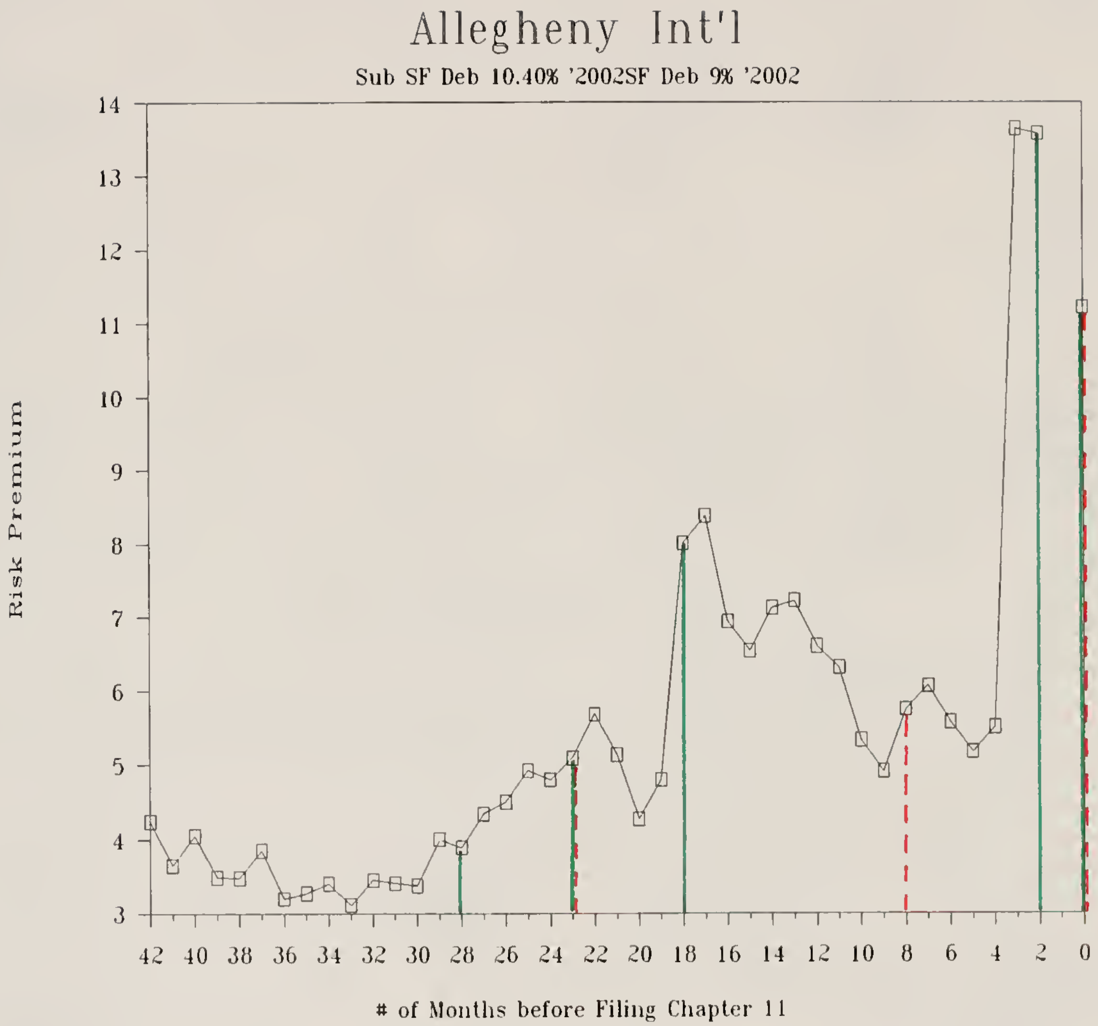

Allegheny Int'l
Sub SF Deb 10.40% '2002SF Deb 9% '2002
Risk Premium
14
13
12
11
10
9
8
7
6
5
4
3
42
40
38
36
34
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
2
0
# of Months before Filing Chapter 11

Figure A-1.

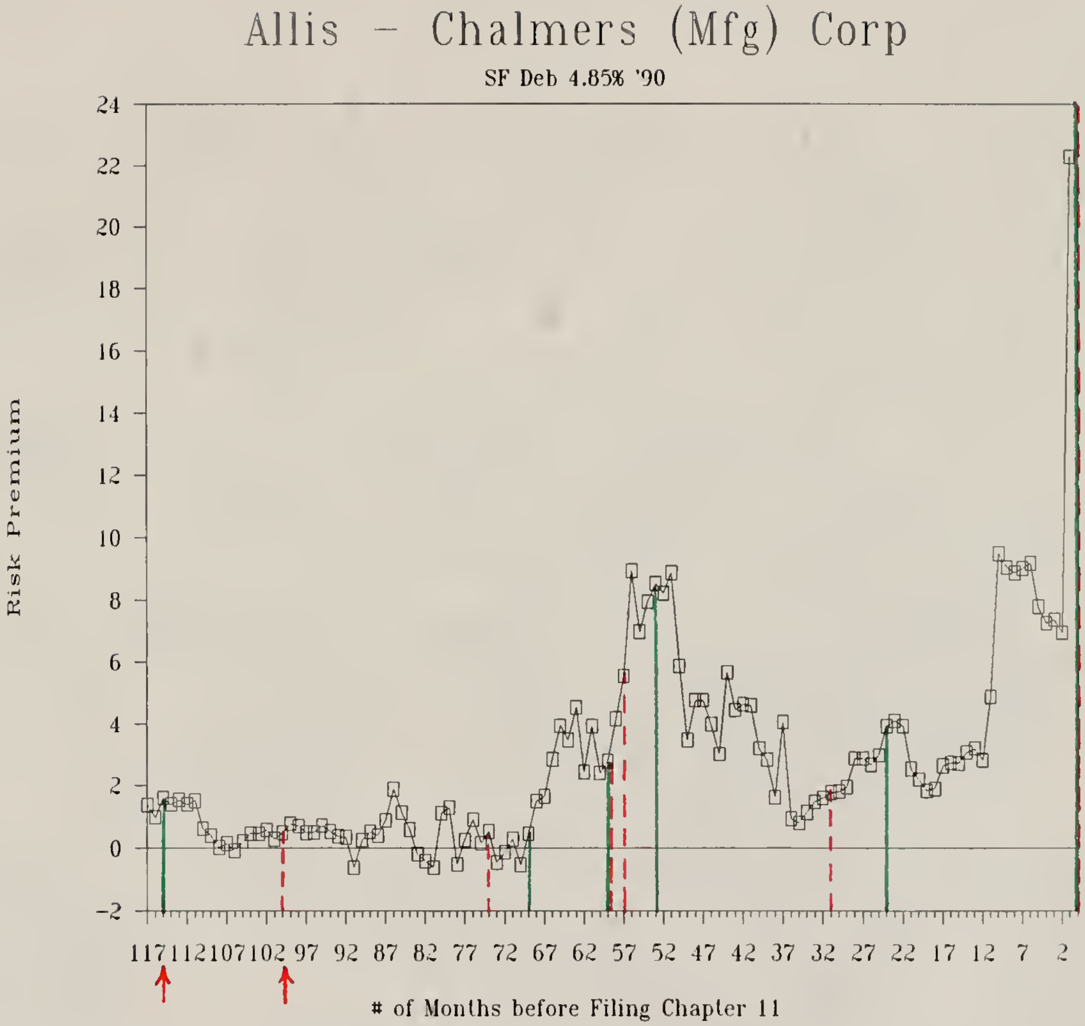

Allis - Chalmers (Mfg) Corp
SF Deb 4.85% '90
Risk Premium
24
22
20
18
16
14
12
10
8
6
4
2
0
-2
117 112 107 102 97 92 87 82 77 72 67 62 57 52 47 42 37 32 27 22 17 12 7 2
# of Months before Filing Chapter 11

Figure A-2.

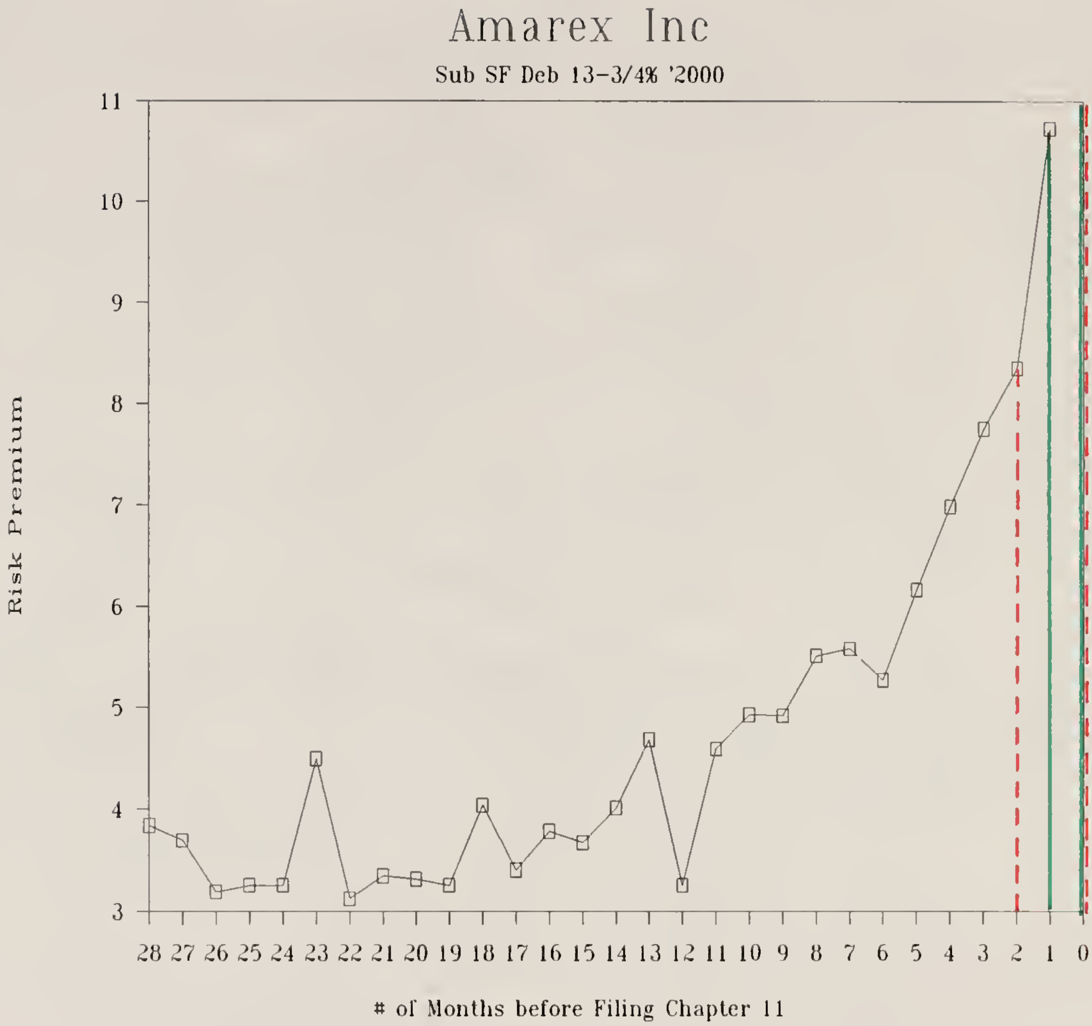

Amarex Inc
Sub SF Deb 13-3/4% '2000
Risk Premium
11
10
9
8
7
6
5
4
3
28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-3.

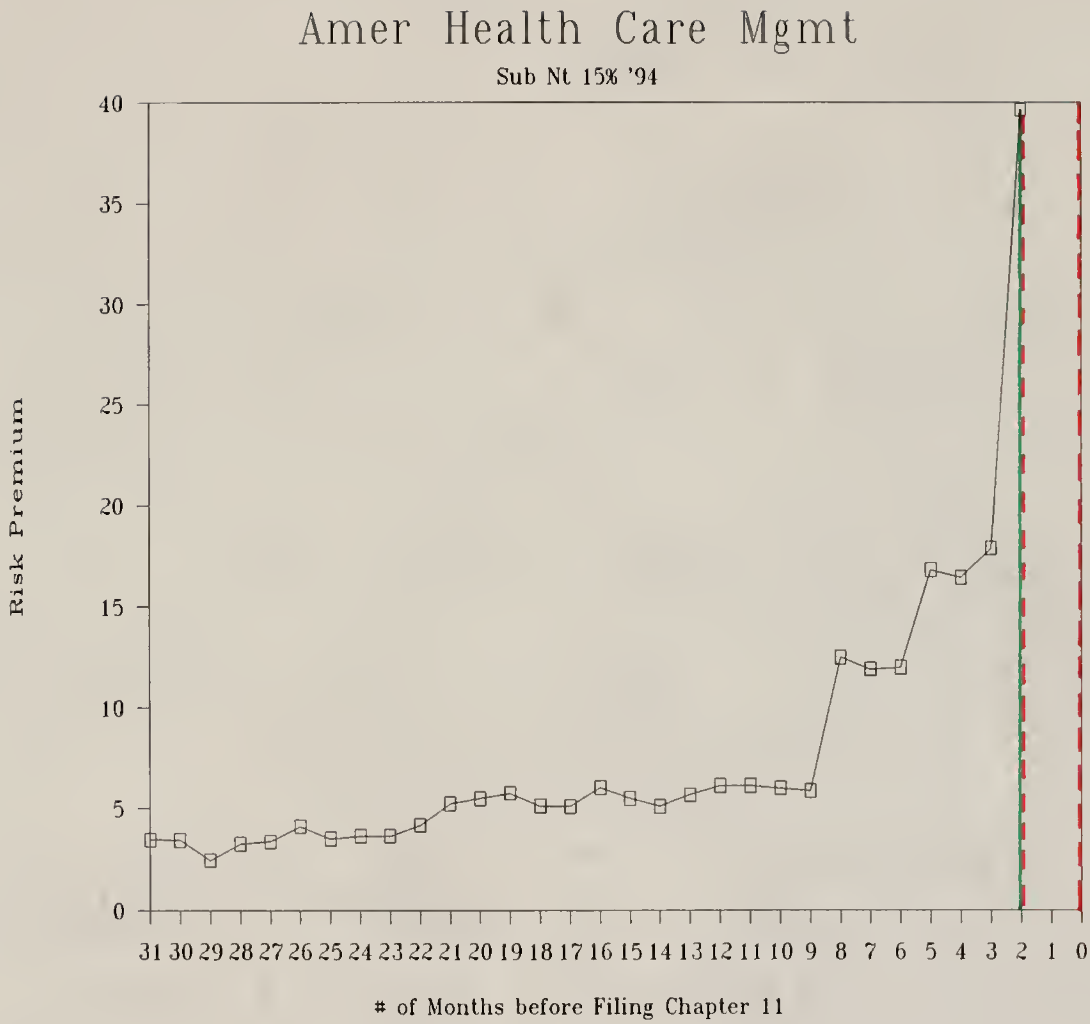

Amer Health Care Mgmt
Sub Nt 15% '94
Risk Premium
40
35
30
25
20
15
10
5
0
31 30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-4.

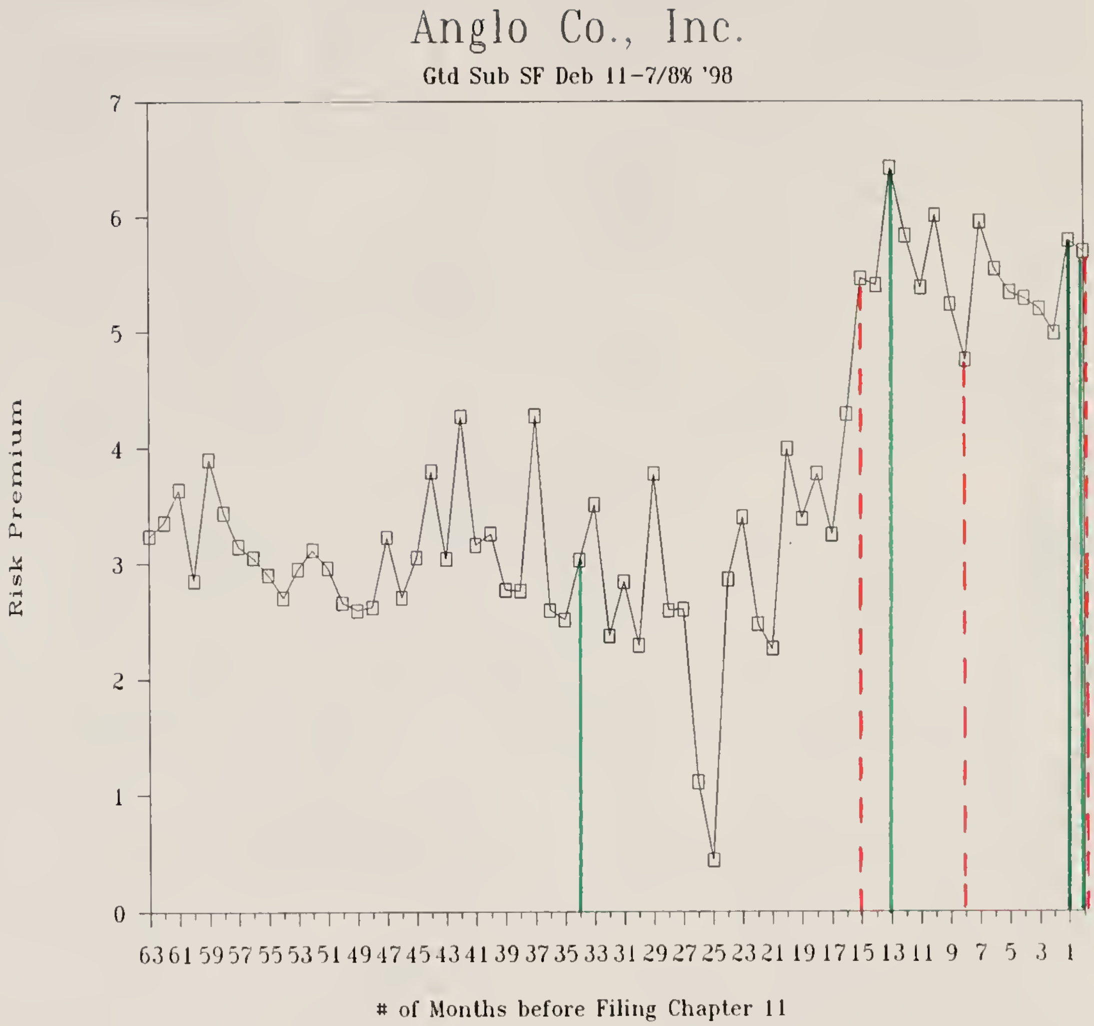

Anglo Co., Inc.
Gtd Sub SF Deb 11-7/8% '98
Risk Premium
7
6
5
4
3
2
1
0
63 61 59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-5.

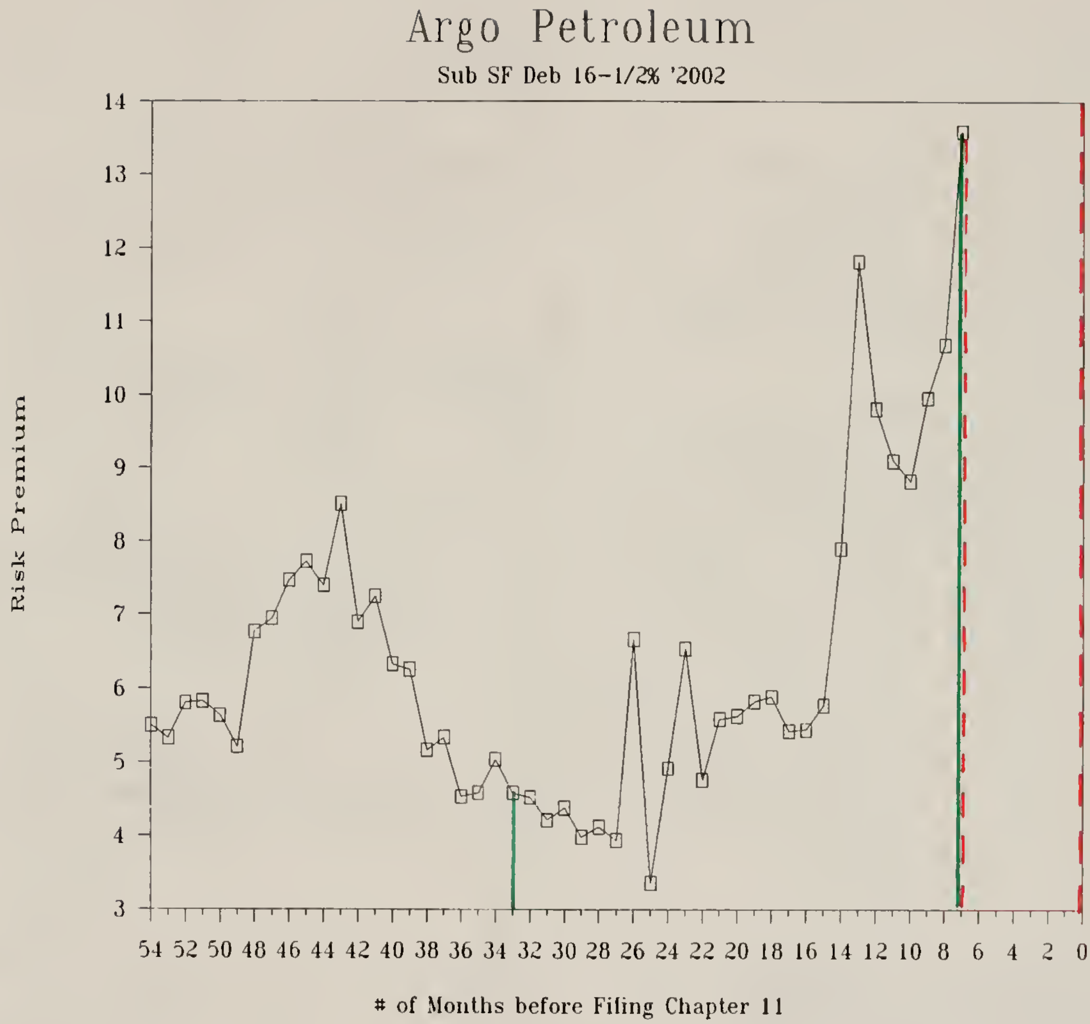
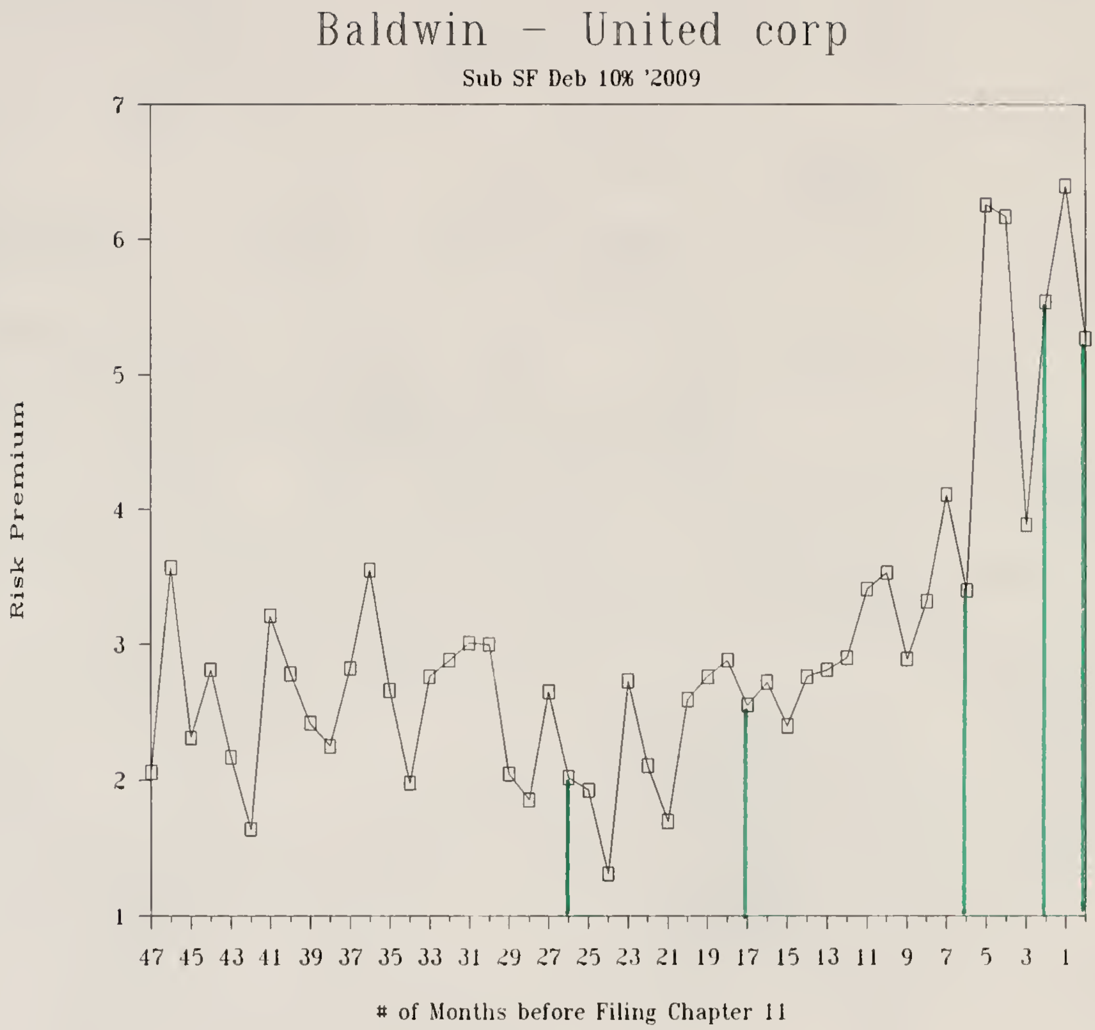

Argo Petroleum
Sub SF Deb 16-1/2% '2002
14
13
12
11
10
9
8
7
6
5
4
3
Risk Premium
54 52 50 48 46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-6.



Baldwin - United corp
Sub SF Deb 10% '2009
Risk Premium
7
6
5
4
3
2
1
47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-7.

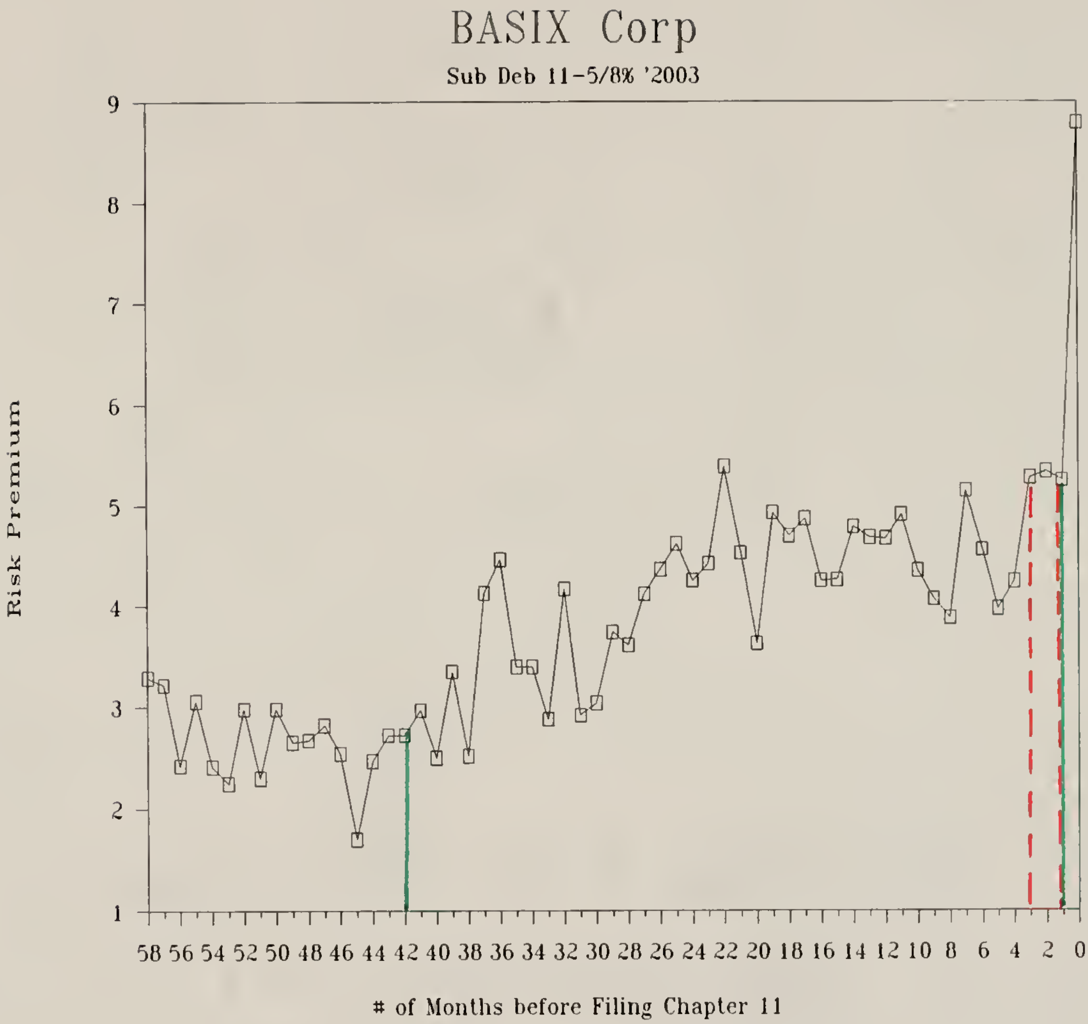

BASIX Corp
Sub Deb 11-5/8% '2003
Risk Premium
9
8
7
6
5
4
3
2
1
58 56 54 52 50 48 46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-8.

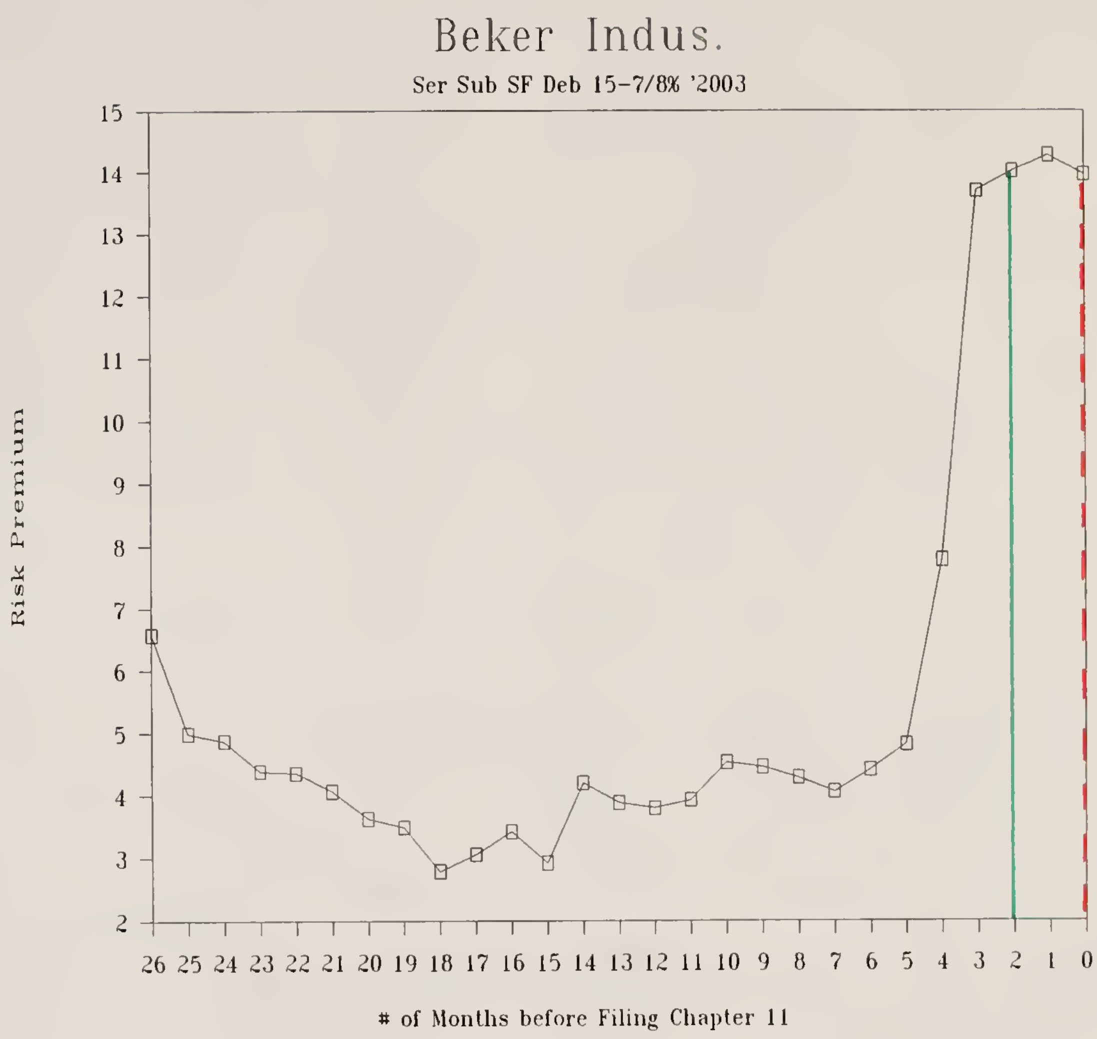
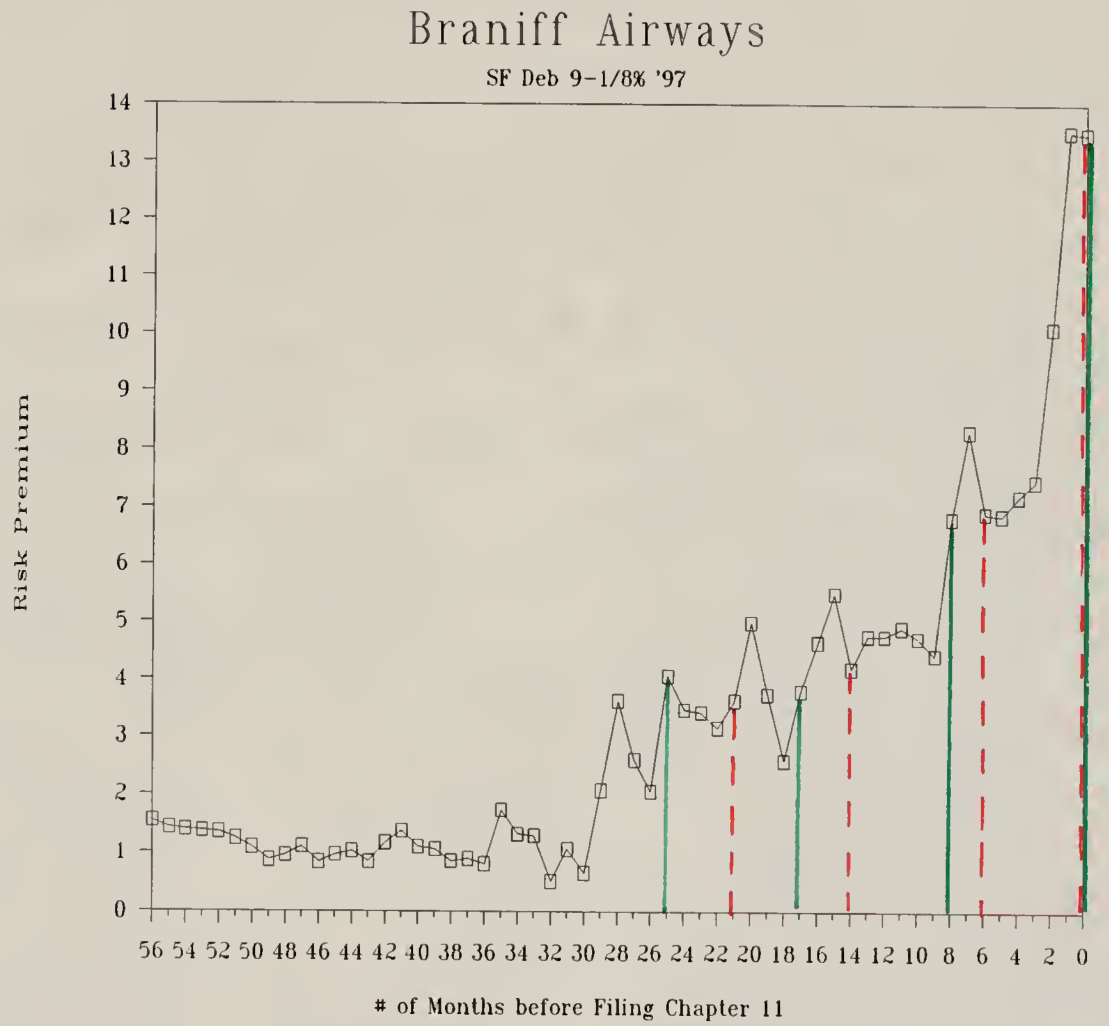

Beker Indus.
Ser Sub SF Deb 15-7/8% '2003
Risk Premium
15
14
13
12
11
10
9
8
7
6
5
4
3
2
26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-9.



Braniff Airways
SF Deb 9-1/8% '97
Risk Premium
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
56 54 52 50 48 46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-10.

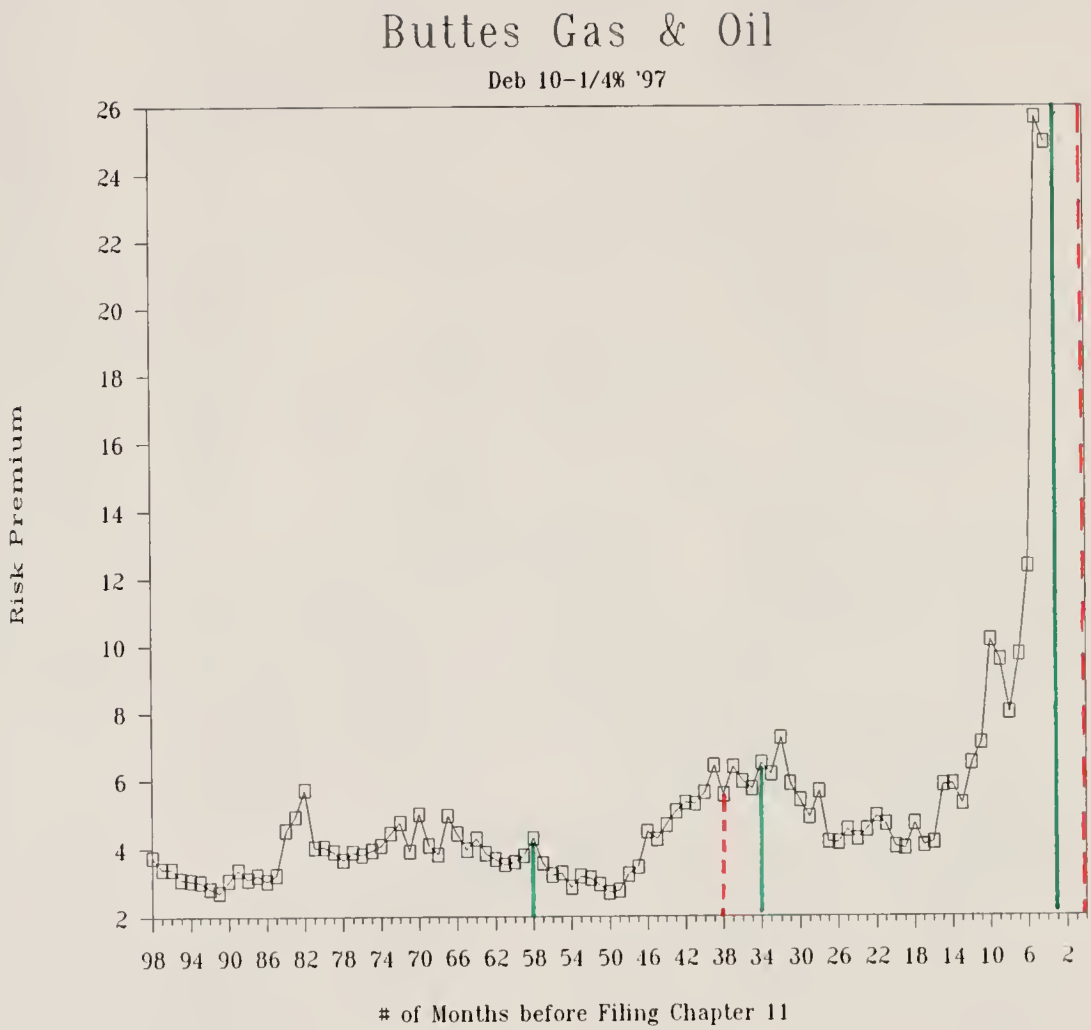

Buttes Gas & Oil
Deb 10-1/4% '97
Risk Premium
26
24
22
20
18
16
14
12
10
8
6
4
2
98 94 90 86 82 78 74 70 66 62 58 54 50 46 42 38 34 30 26 22 18 14 10 6 2
# of Months before Filing Chapter 11

Figure A-11.

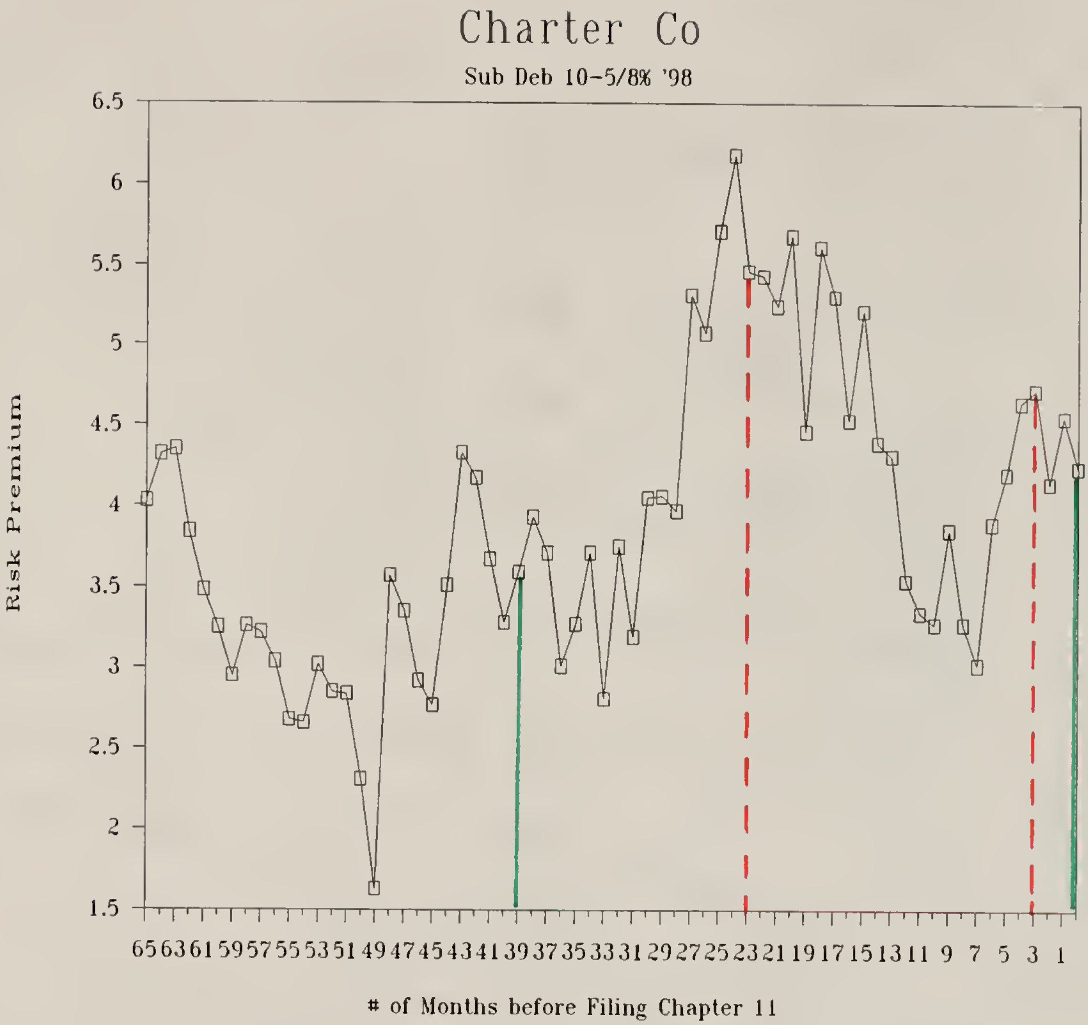
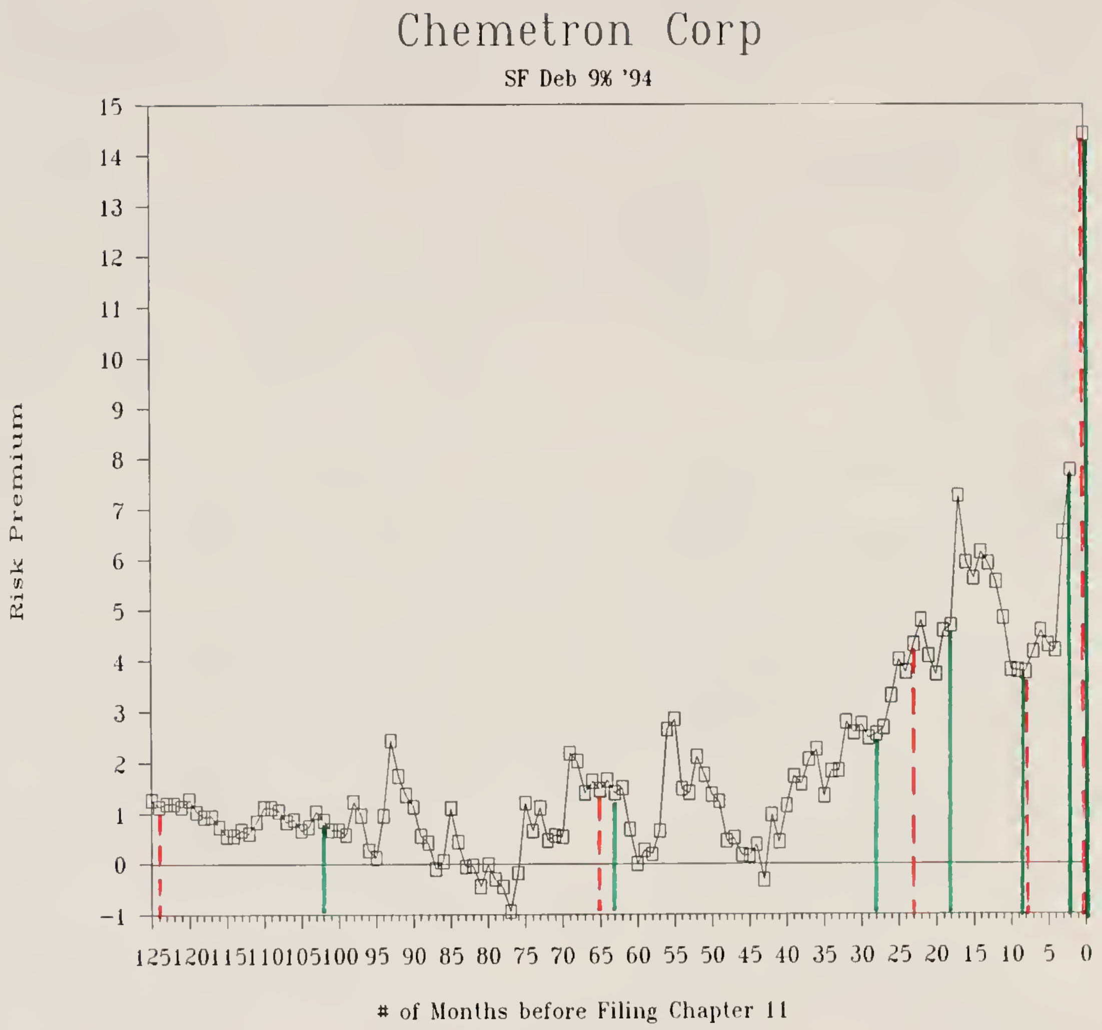

Charter Co
Sub Deb 10-5/8% '98
Risk Premium
6.5
6
5.5
5
4.5
4
3.5
3
2.5
2
1.5
65 63 61 59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-12.



Chemetron Corp
SF Deb 9% '94
Risk Premium
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
-1
125
120
115
110
105
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
# of Months before Filing Chapter 11

Figure A-13.

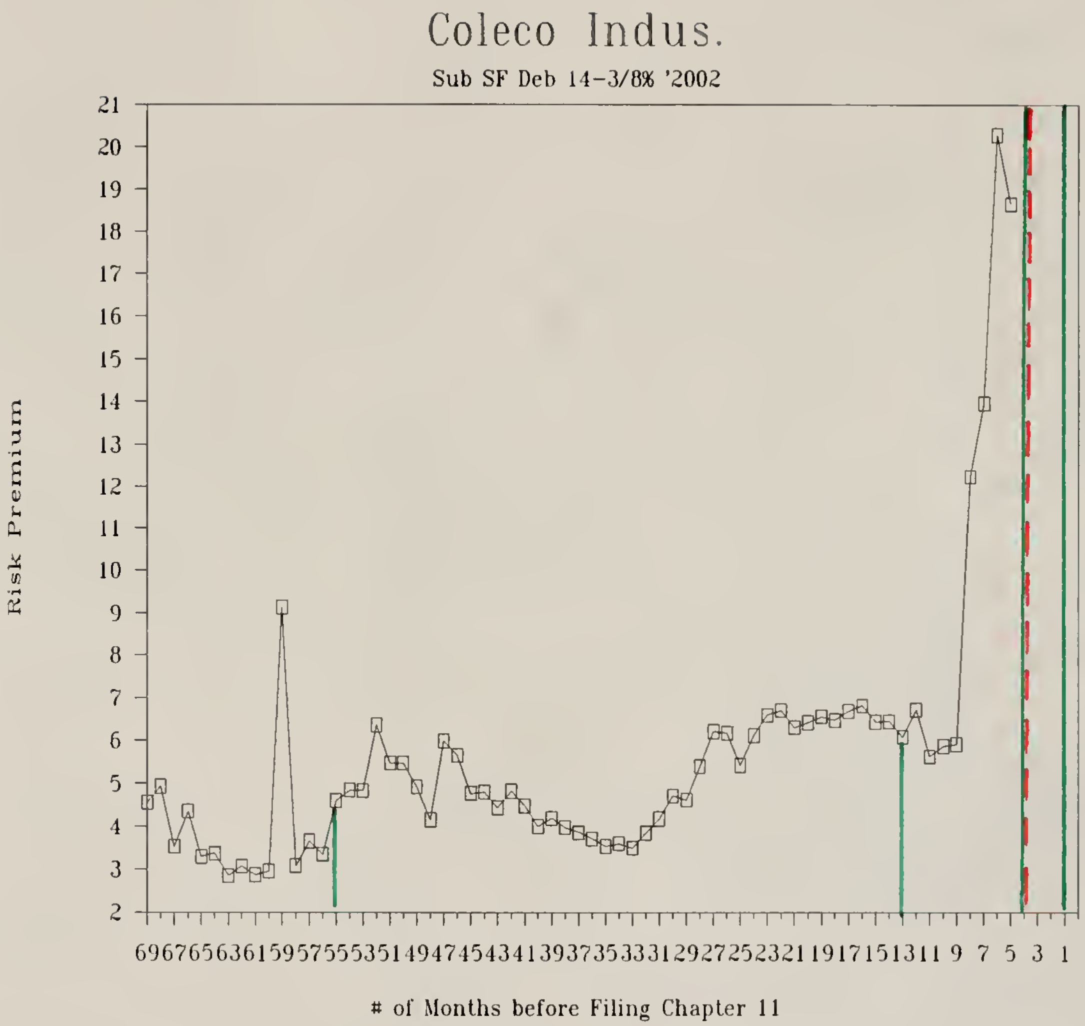
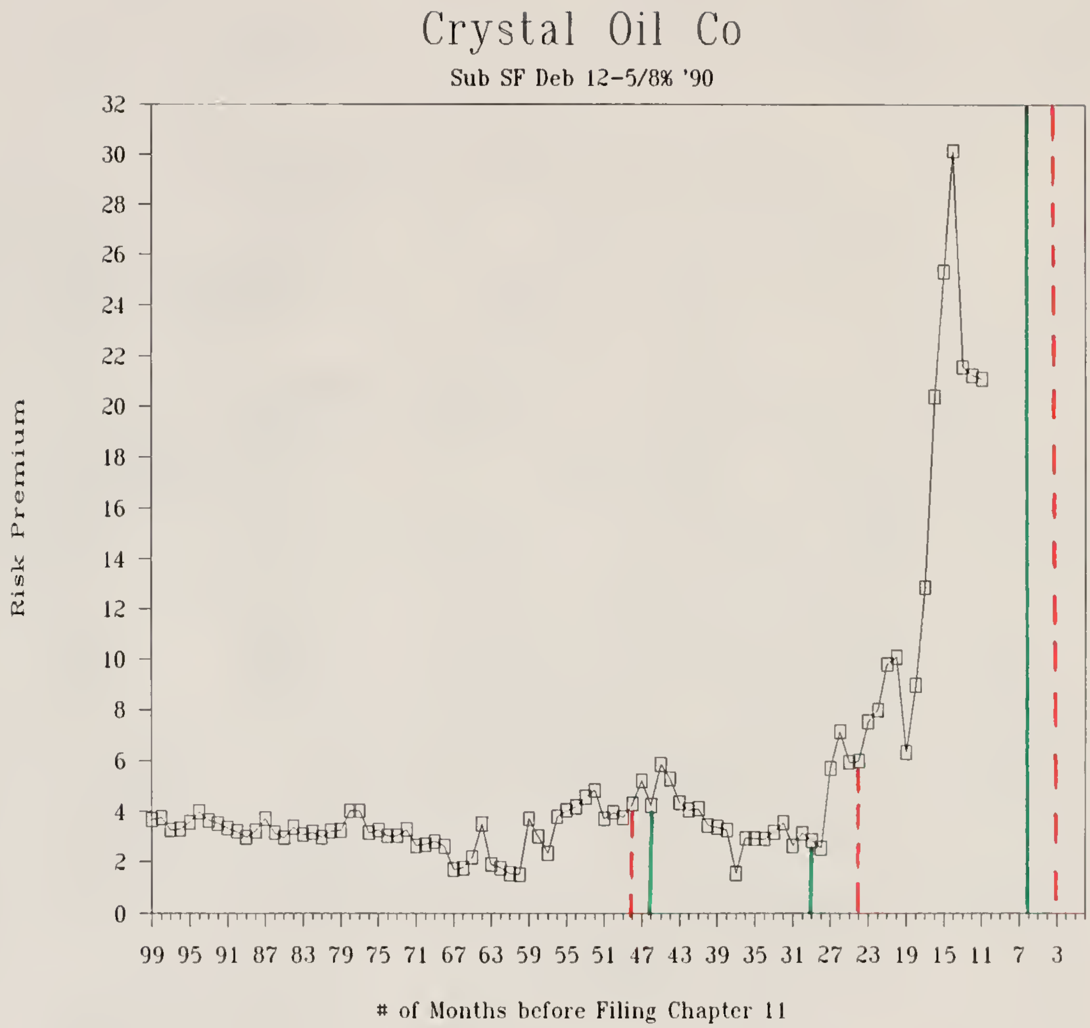
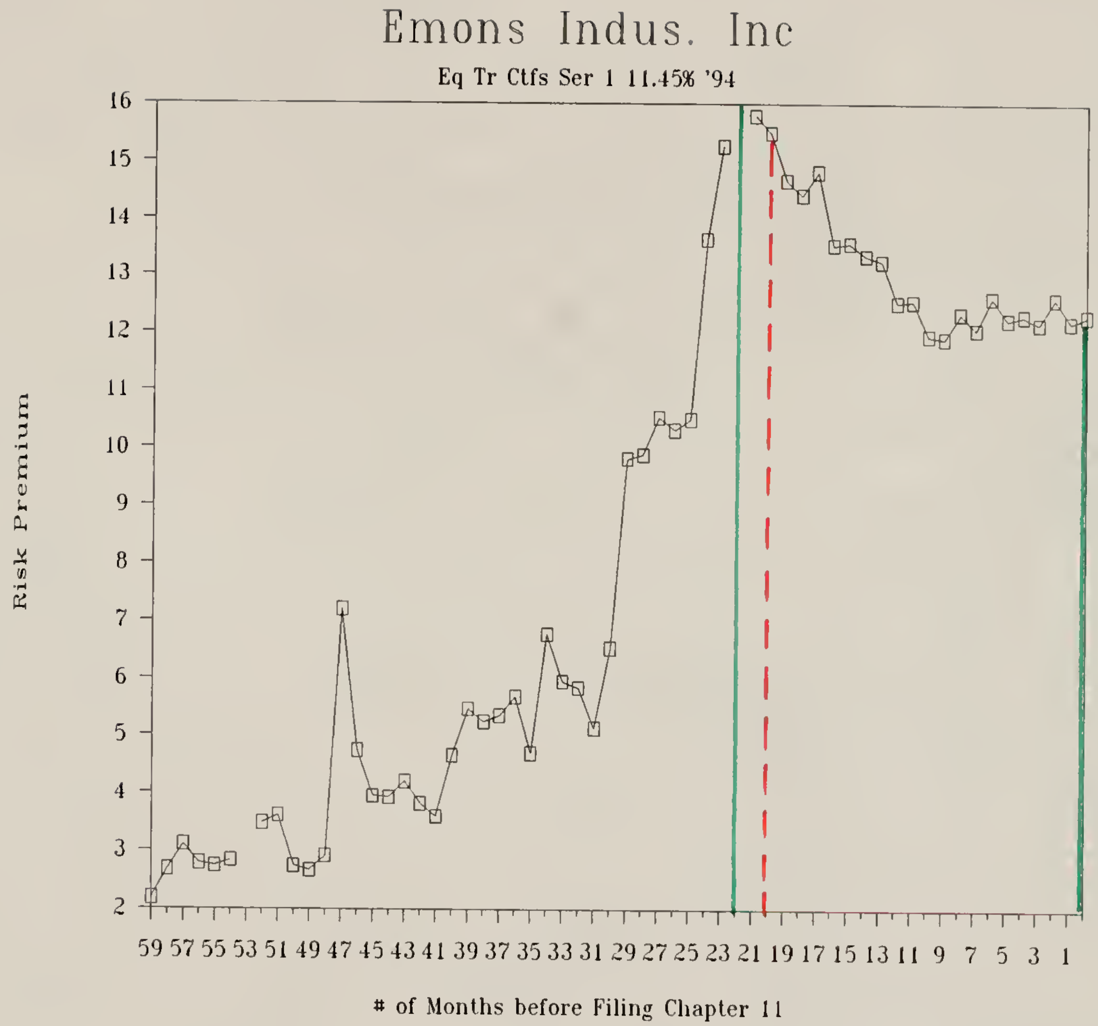

Coleco Indus.
Sub SF Deb 14-3/8% '2002
Risk Premium
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
69676563615957555351494745434139373533312927252321191715131l 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-14.



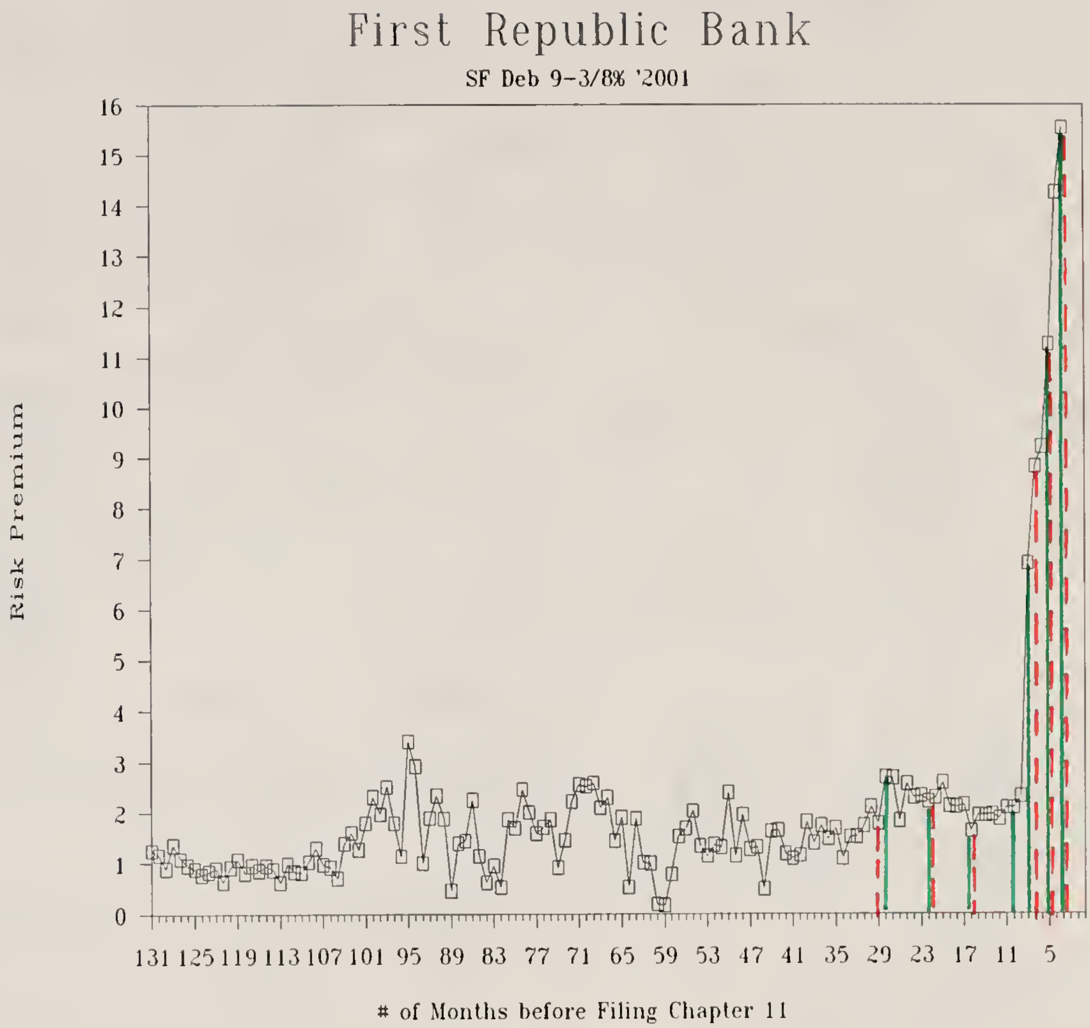
Crystal Oil Co
Sub SF Deb 12-5/8% '90
Risk Premium
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
99 95 91 87 83 79 75 71 67 63 59 55 51 47 43 39 35 31 27 23 19 15 11 7 3
# of Months before Filing Chapter 11

Figure A-15.



Emons Indus. Inc
Eq Tr Ctfs Ser 1 11.45% '94
Risk Premium
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-16.



First Republic Bank
SF Deb 9-3/8% '2001
Risk Premium
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
131 125 119 113 107 101 95 89 83 77 71 65 59 53 47 41 35 29 23 17 11 5
# of Months before Filing Chapter 11

Figure A-17.

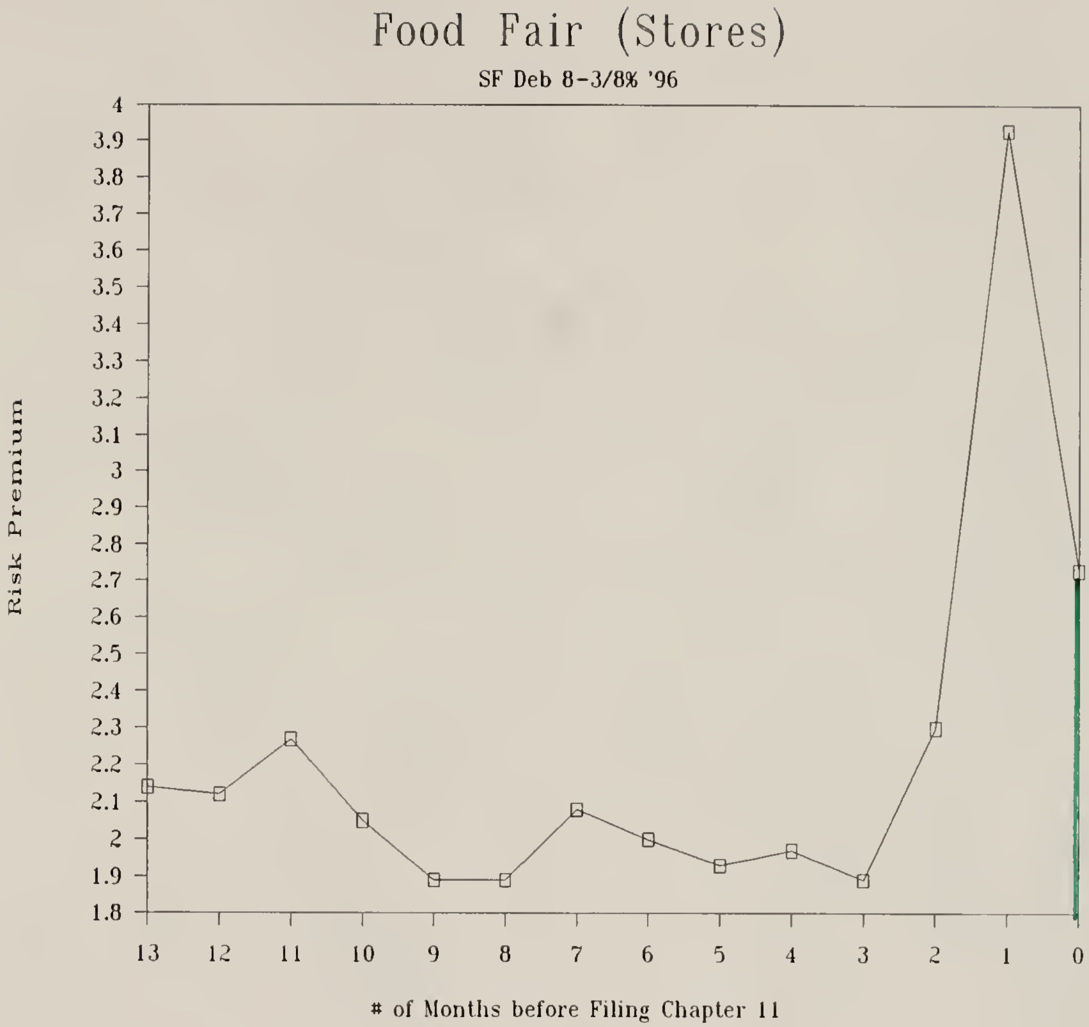

Food Fair (Stores)
SF Deb 8-3/8% '96
Risk Premium
4
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
1.9
1.8
13
12
11
10
9
8
7
6
5
4
3
2
1
0
# of Months before Filing Chapter 11

Figure A-18.

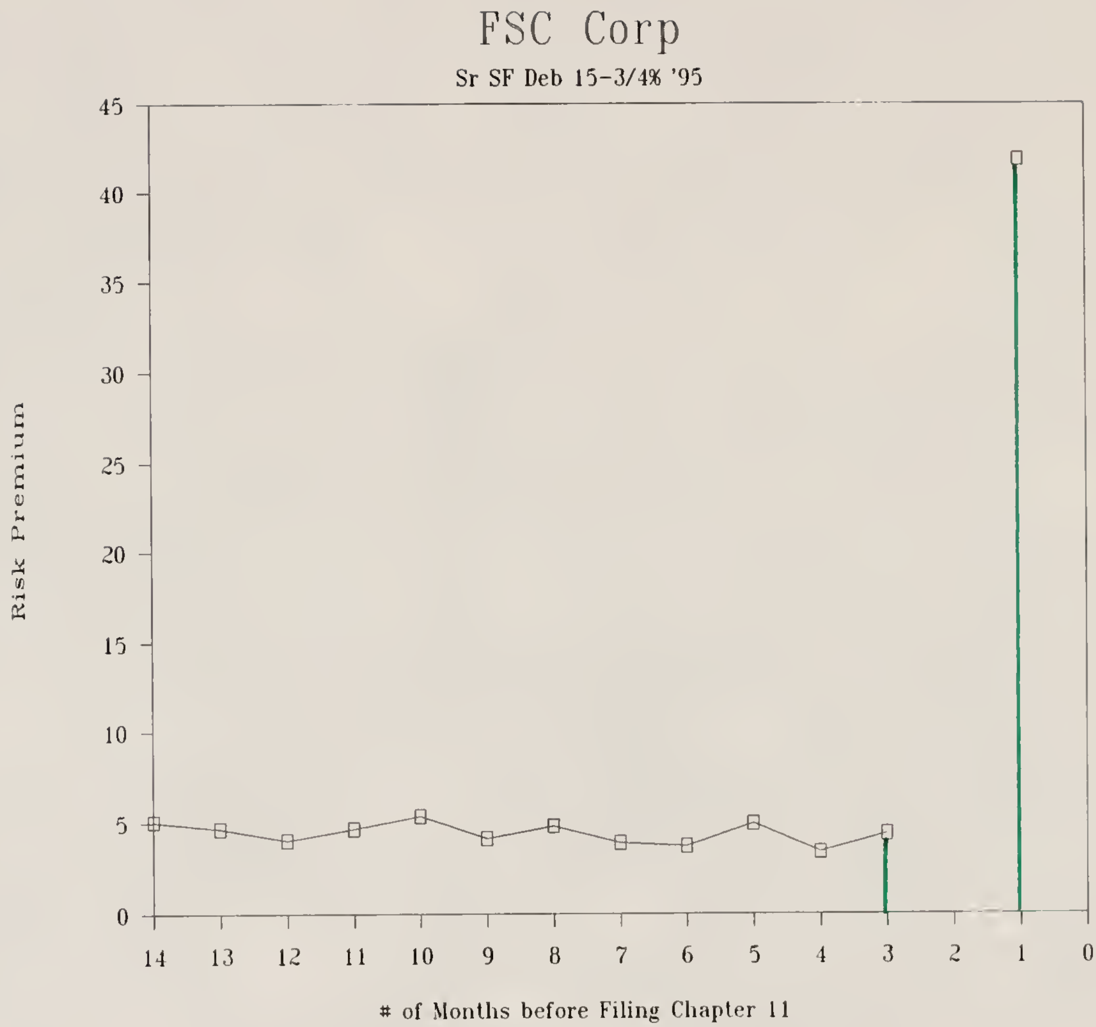
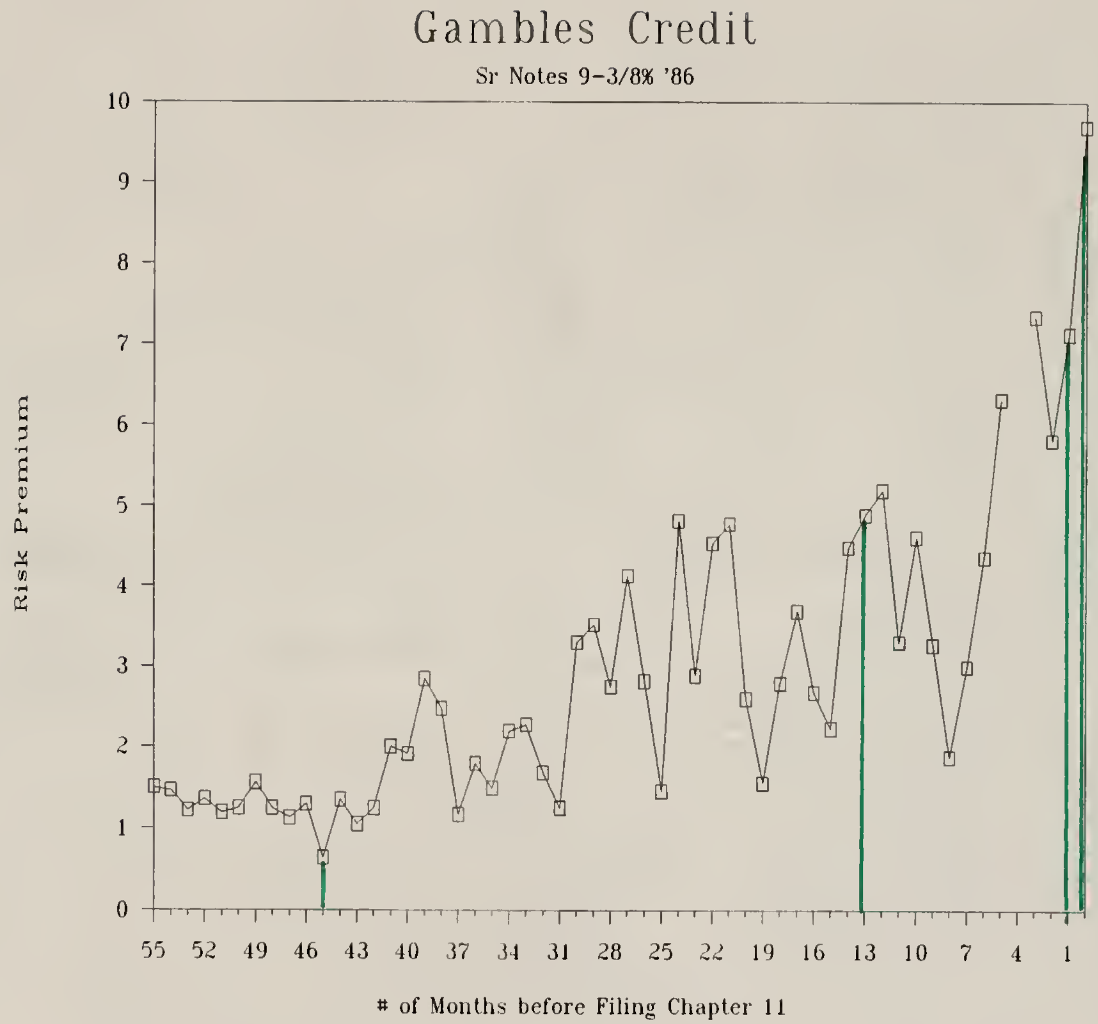
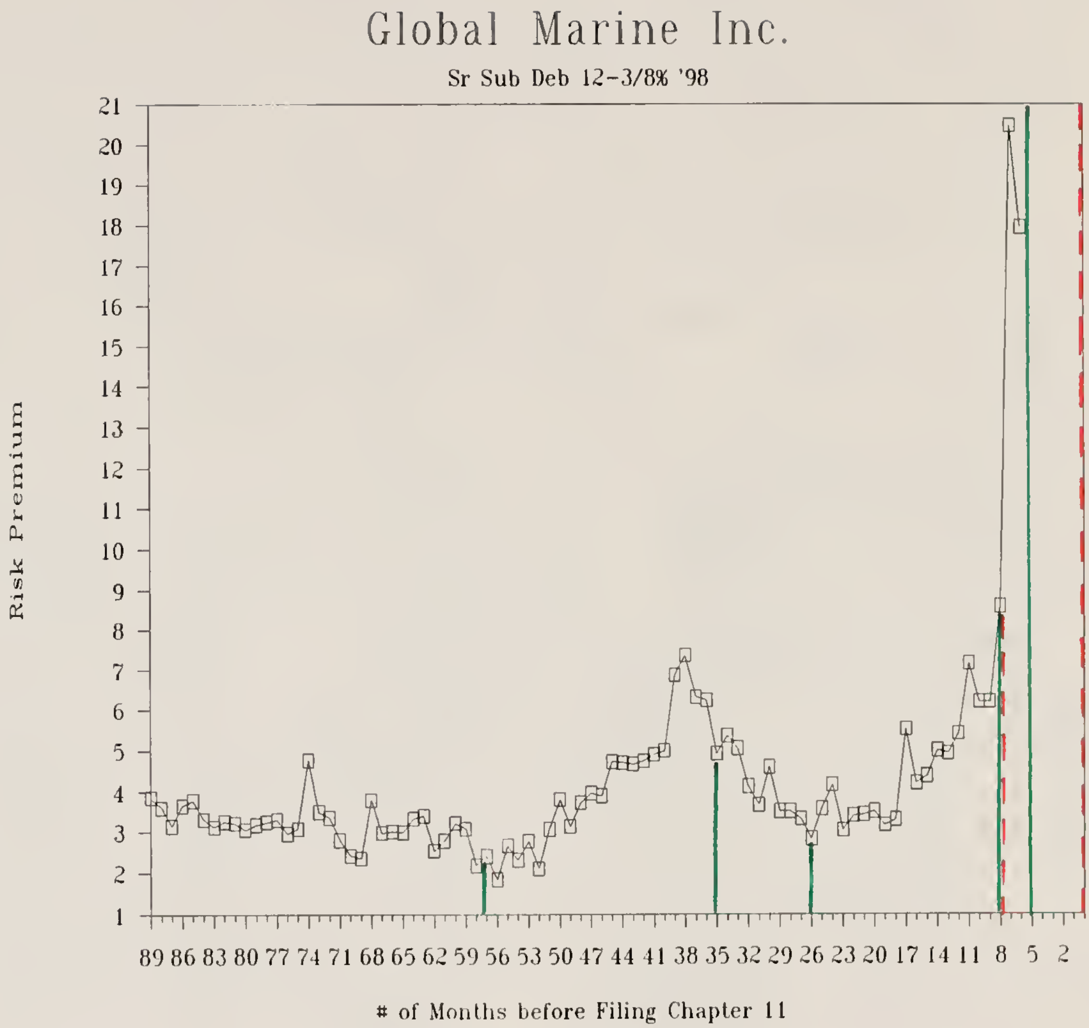

FSC Corp
Sr SF Deb 15-3/4% '95
Risk Premium
45
40
35
30
25
20
15
10
5
0
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
# of Months before Filing Chapter 11

Figure A-19.



Gambles Credit
Sr Notes 9-3/8% '86
Risk Premium
0
1
2
3
4
5
6
7
8
9
10
55
52
49
46
43
40
37
34
31
28
25
22
19
16
13
10
7
4
1
# of Months before Filing Chapter 11

Figure A-20.



Global Marine Inc.
Sr Sub Deb 12-3/8% '98
Risk Premium
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
89 86 83 80 77 74 71 68 65 62 59 56 53 50 47 44 41 38 35 32 29 26 23 20 17 14 11 8 5 2
# of Months before Filing Chapter 11

Figure A-21.

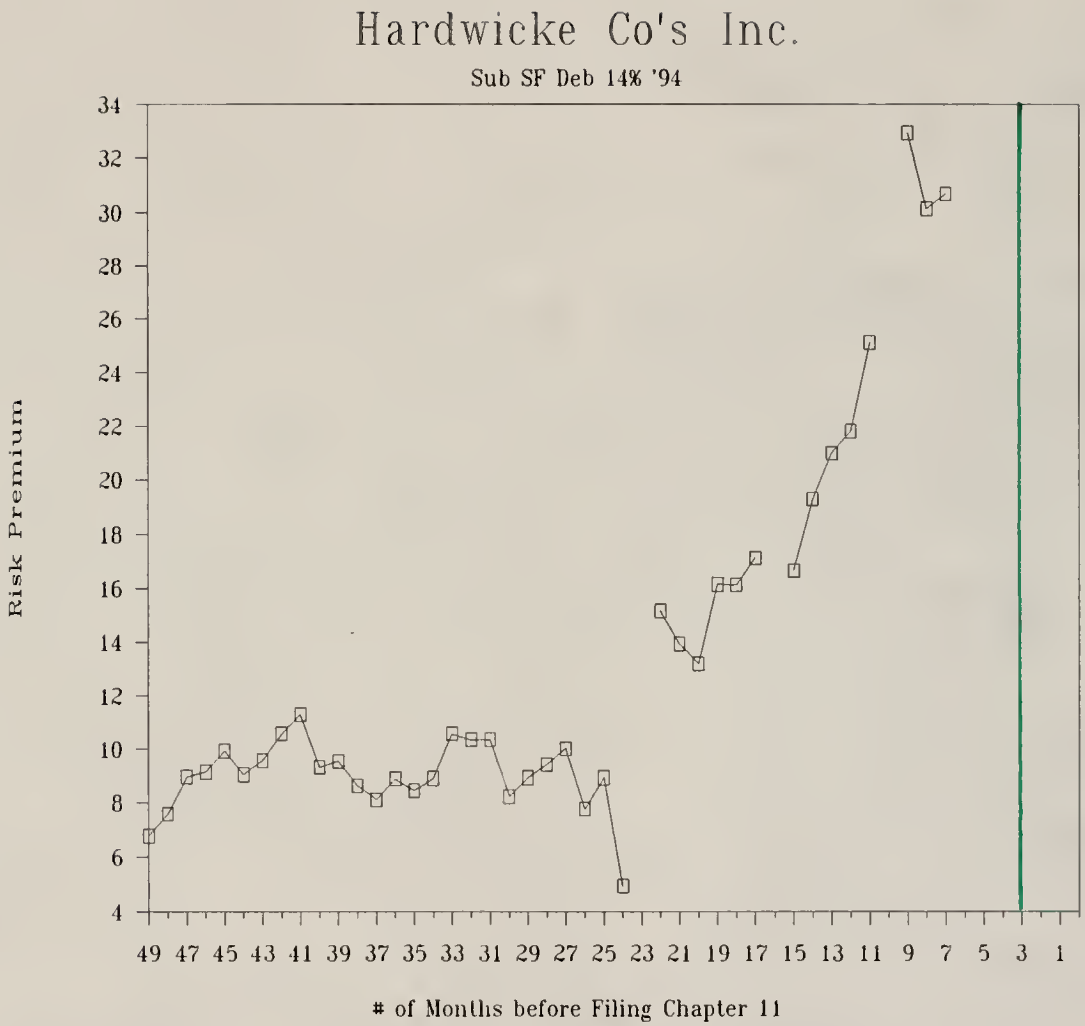
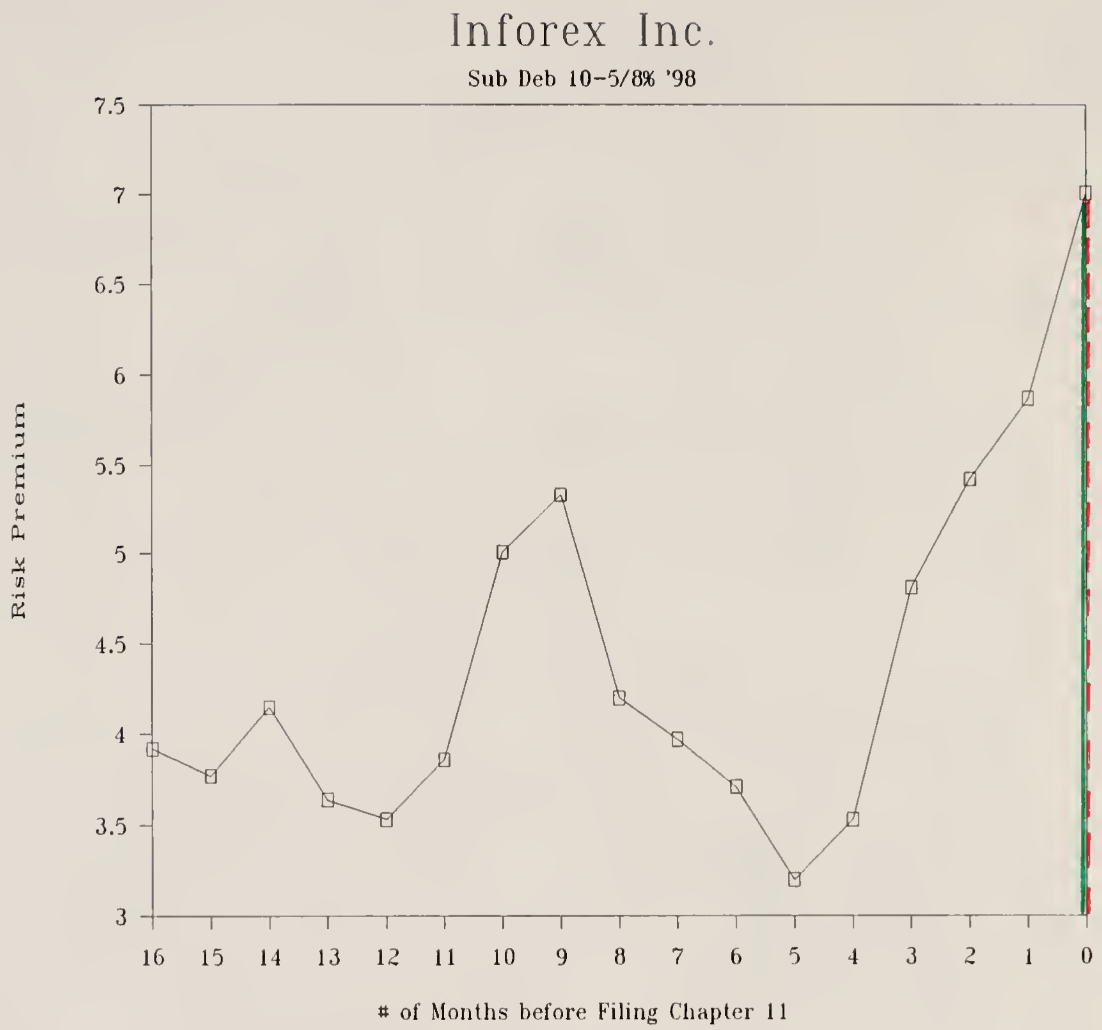
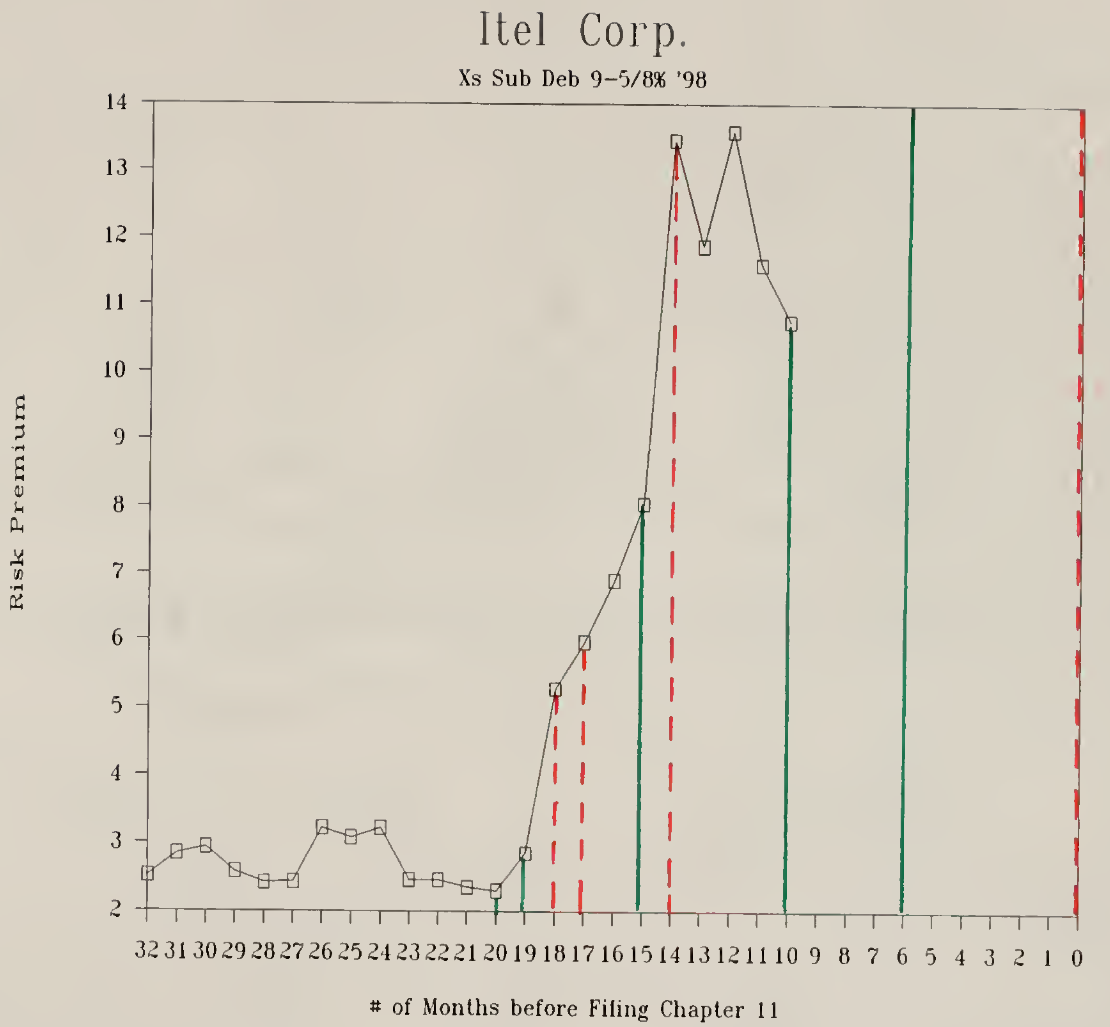

Hardwicke Co's Inc.
Sub SF Deb 14% '94
Risk Premium
34
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-22.



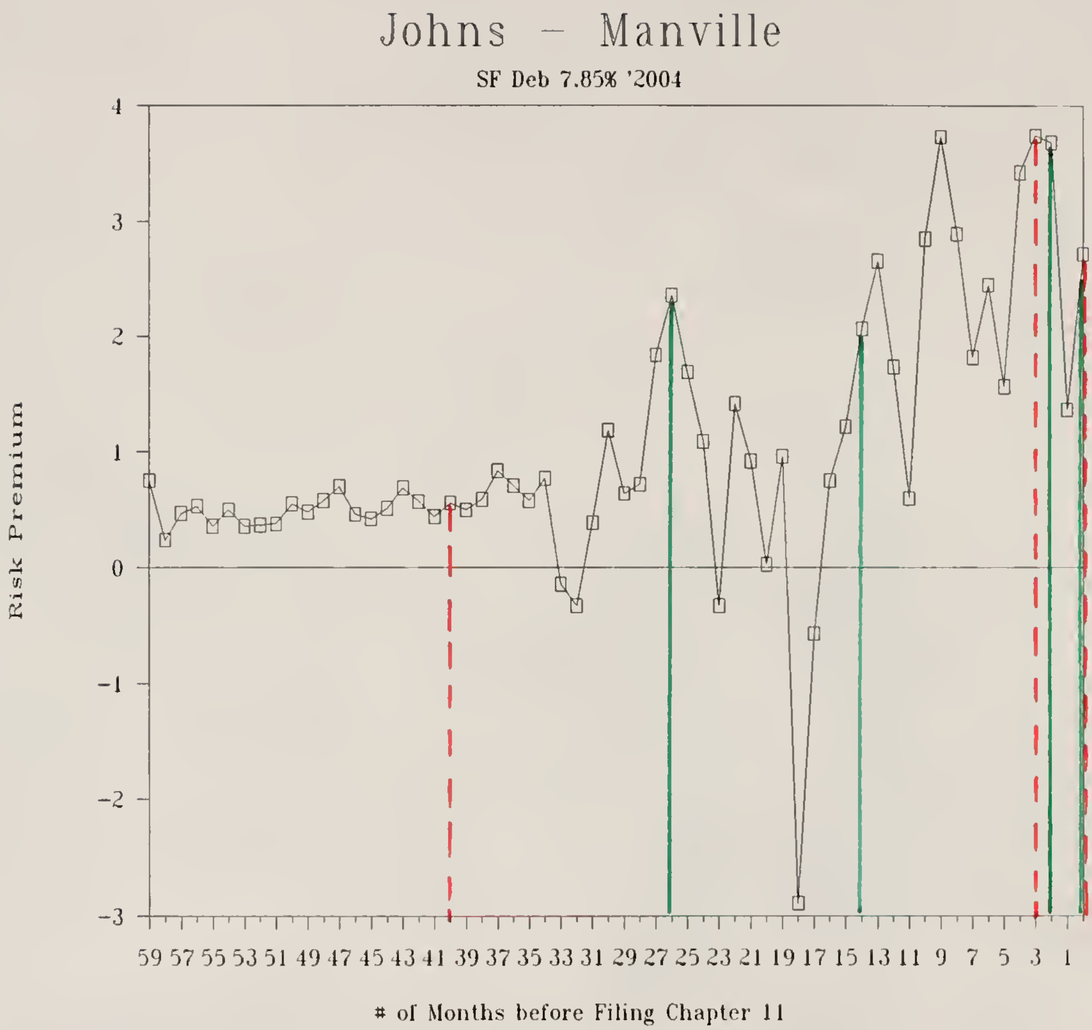
Inforex Inc.
Sub Deb 10-5/8% '98
Risk Premium
7.5
7
6.5
6
5.5
5
4.5
4
3.5
3
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
# of Months before Filing Chapter 11

Figure A-23.



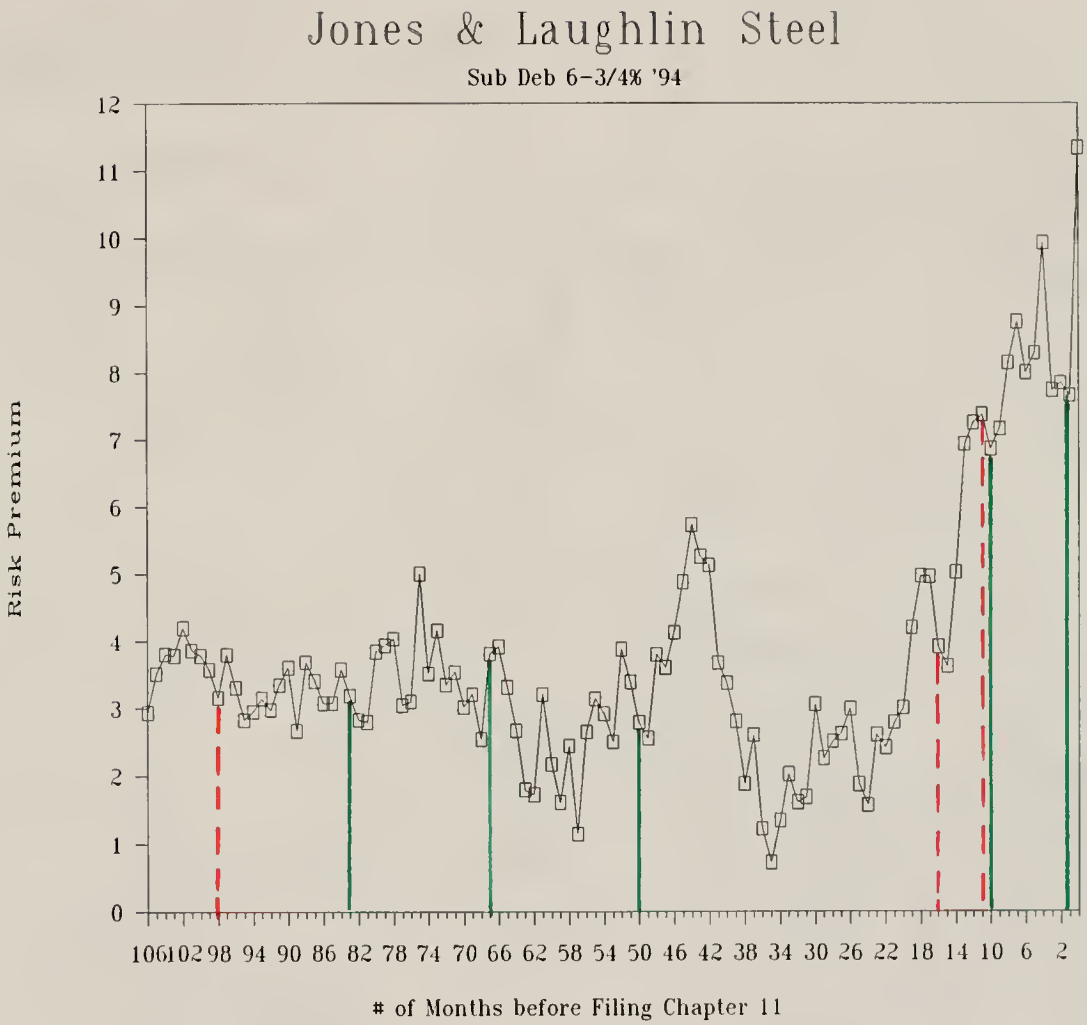
Itel Corp.
Xs Sub Deb 9-5/8% '98
Risk Premium
14
13
12
11
10
9
8
7
6
5
4
3
2
32 31 30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-24.



Johns - Manville
SF Deb 7.85% '2004
Risk Premium
4
3
2
1
0
-1
-2
-3
59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-25.



Jones & Laughlin Steel
Sub Deb 6-3/4% '94
Risk Premium
12
11
10
9
8
7
6
5
4
3
2
1
0
106102 98 94 90 86 82 78 74 70 66 62 58 54 50 46 42 38 34 30 26 22 18 14 10 6 2
# of Months before Filing Chapter 11

Figure A-26.

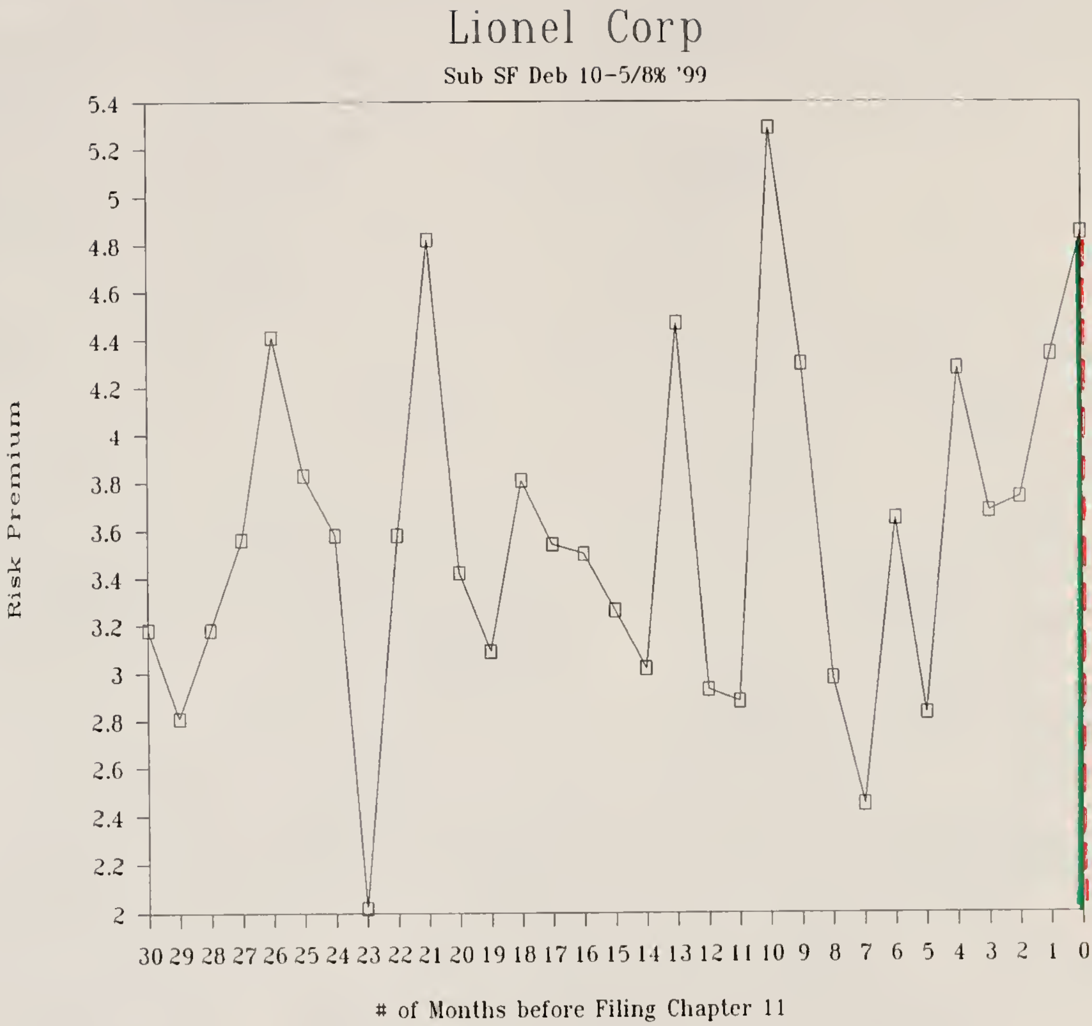
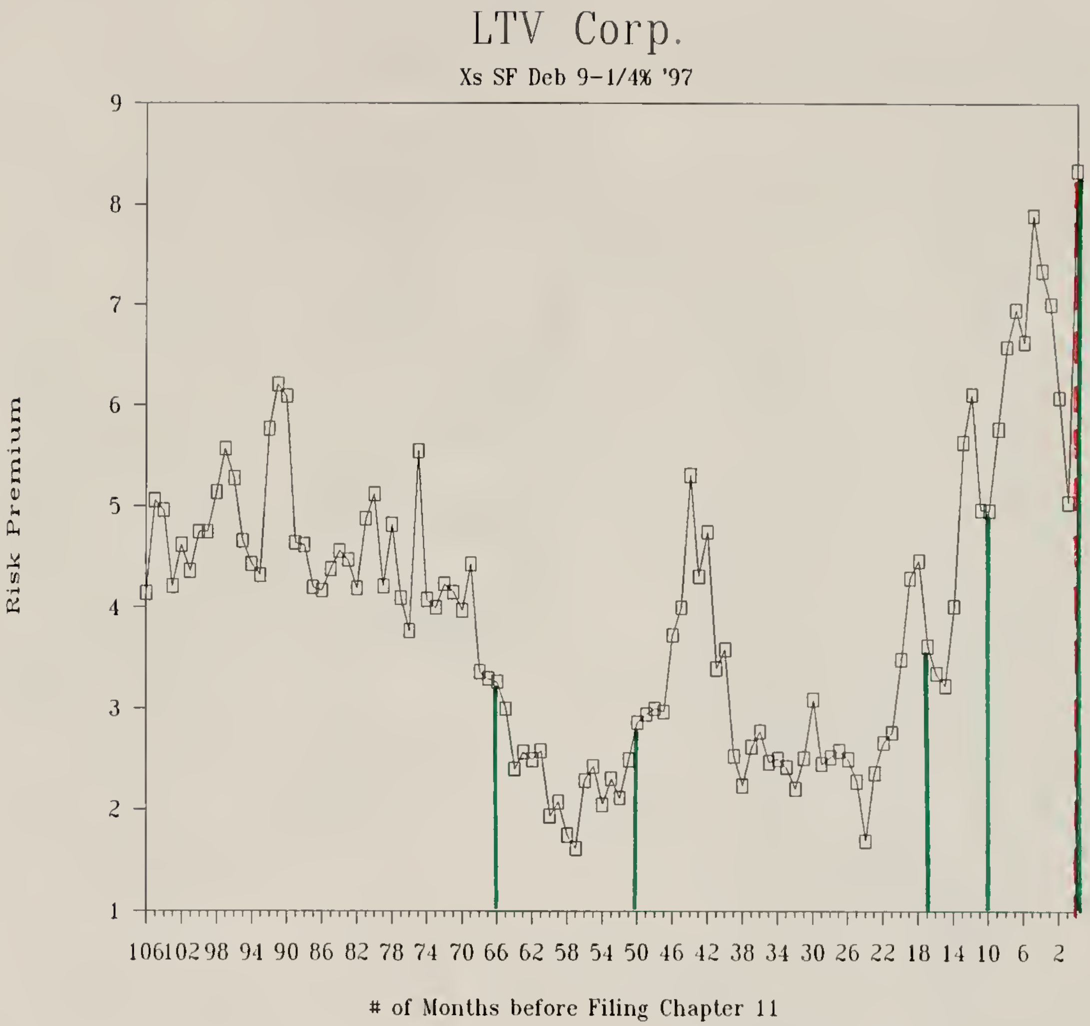
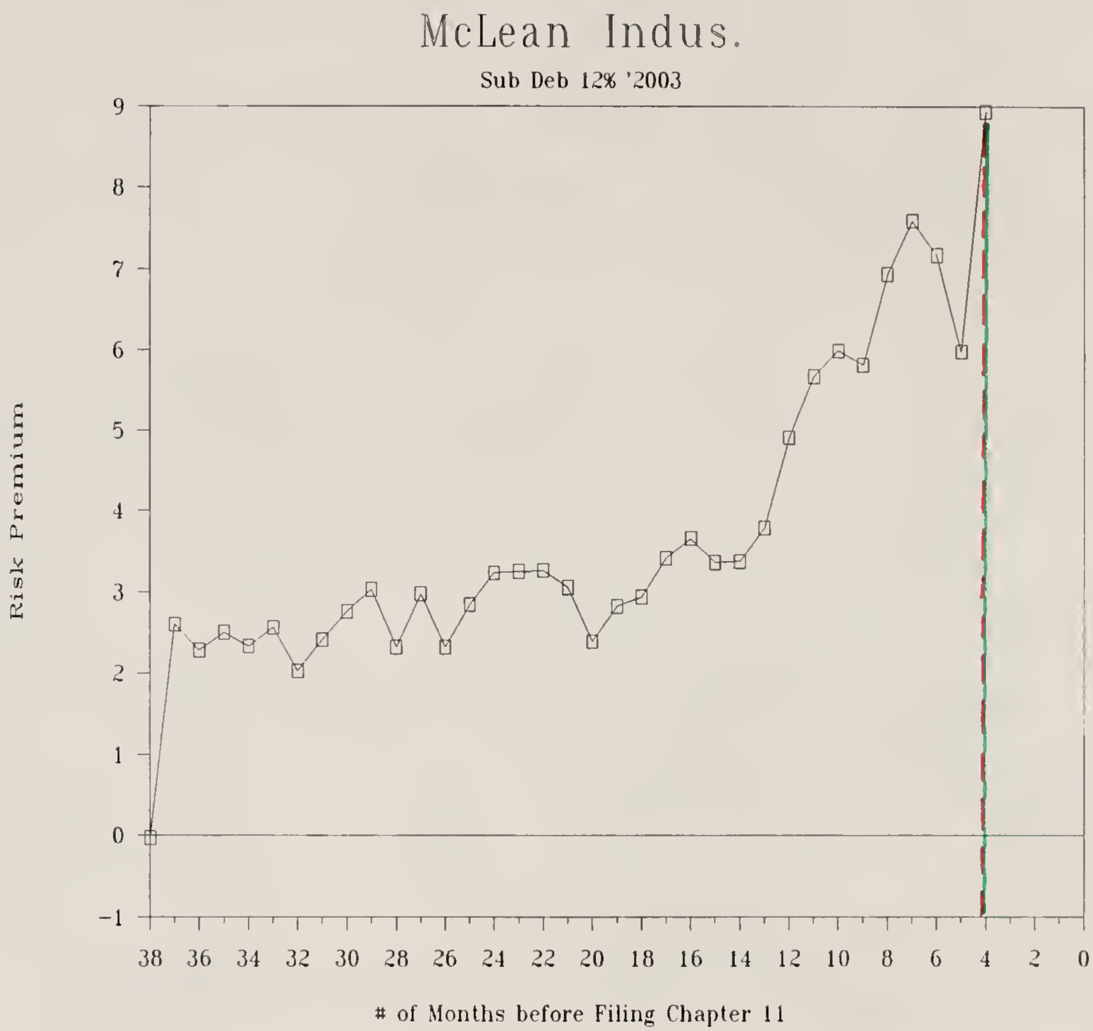

Lionel Corp
Sub SF Deb 10-5/8% '99
Risk Premium
5.4
5.2
5
4.8
4.6
4.4
4.2
4
3.8
3.6
3.4
3.2
3
2.8
2.6
2.4
2.2
2
30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-27.



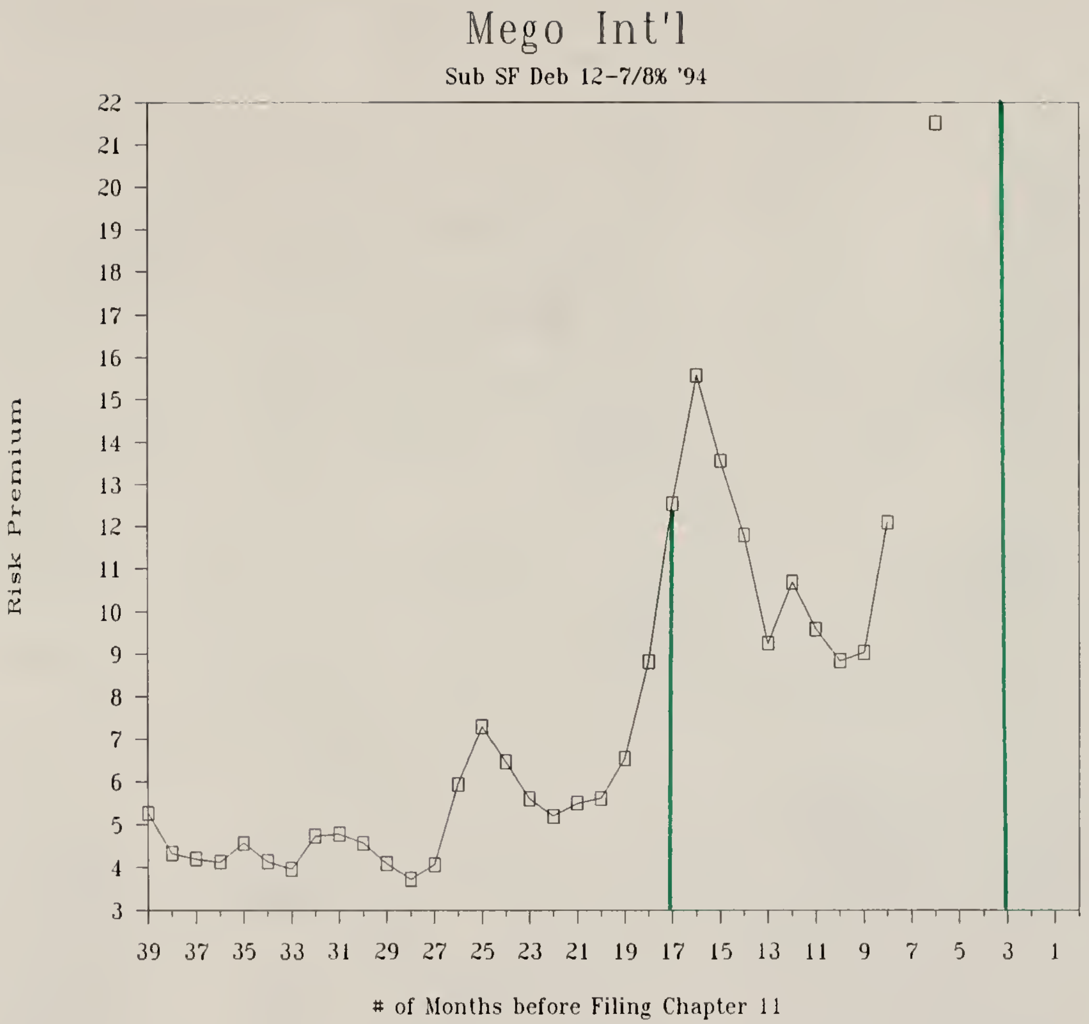
LTV Corp.
Xs SF Deb 9-1/4% '97
9
8
7
6
5
4
3
2
1
Risk Premium
106102 98 94 90 86 82 78 74 70 66 62 58 54 50 46 42 38 34 30 26 22 18 14 10 6 2
# of Months before Filing Chapter 11

Figure A-28.



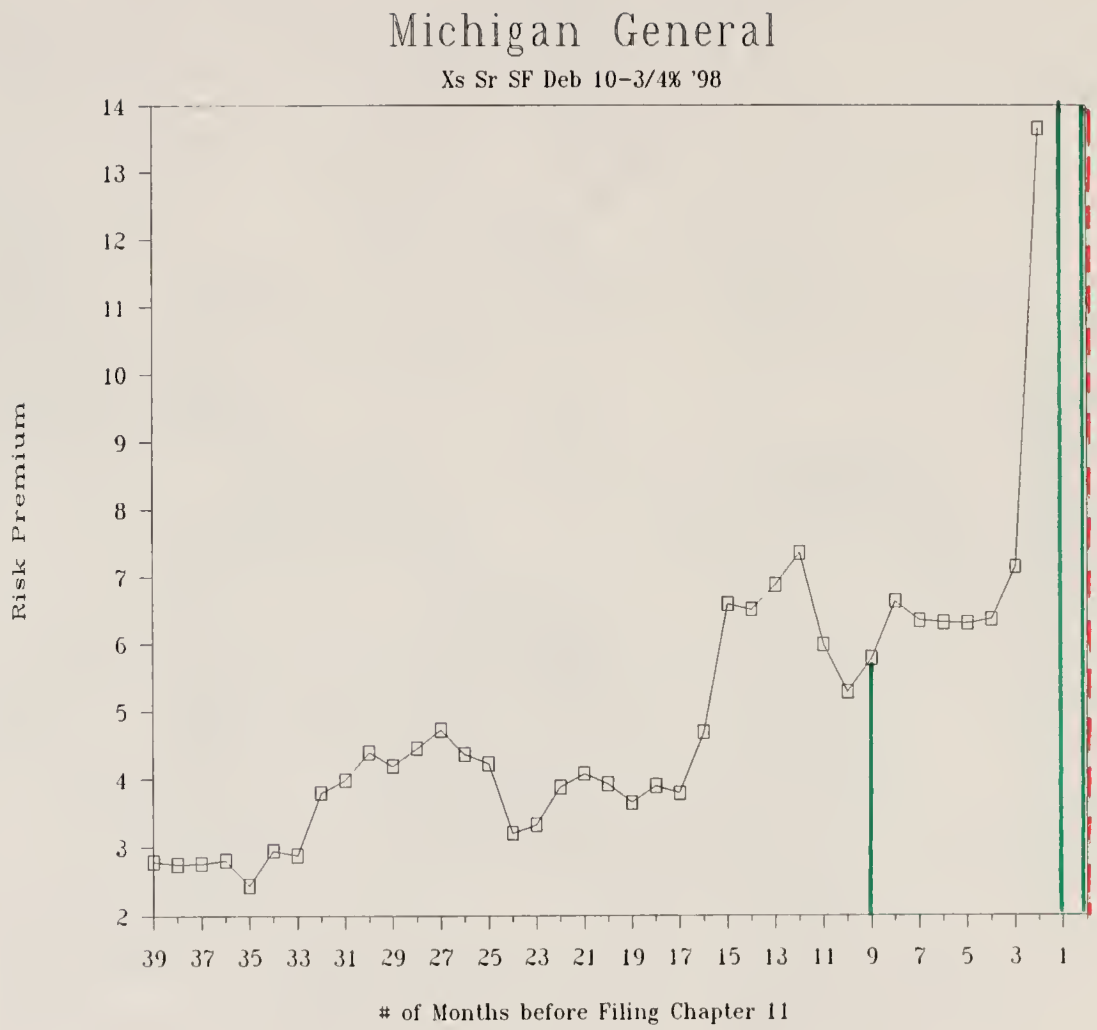
McLean Indus.
Sub Deb 12% '2003
Risk Premium
9
8
7
6
5
4
3
2
1
0
−1
38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-29.



Mego Int'l
Sub SF Deb 12-7/8% '94
Risk Premium
22
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-30.



Michigan General
Xs Sr SF Deb 10-3/4% '98
Risk Premium
14
13
12
11
10
9
8
7
6
5
4
3
2
39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-31.

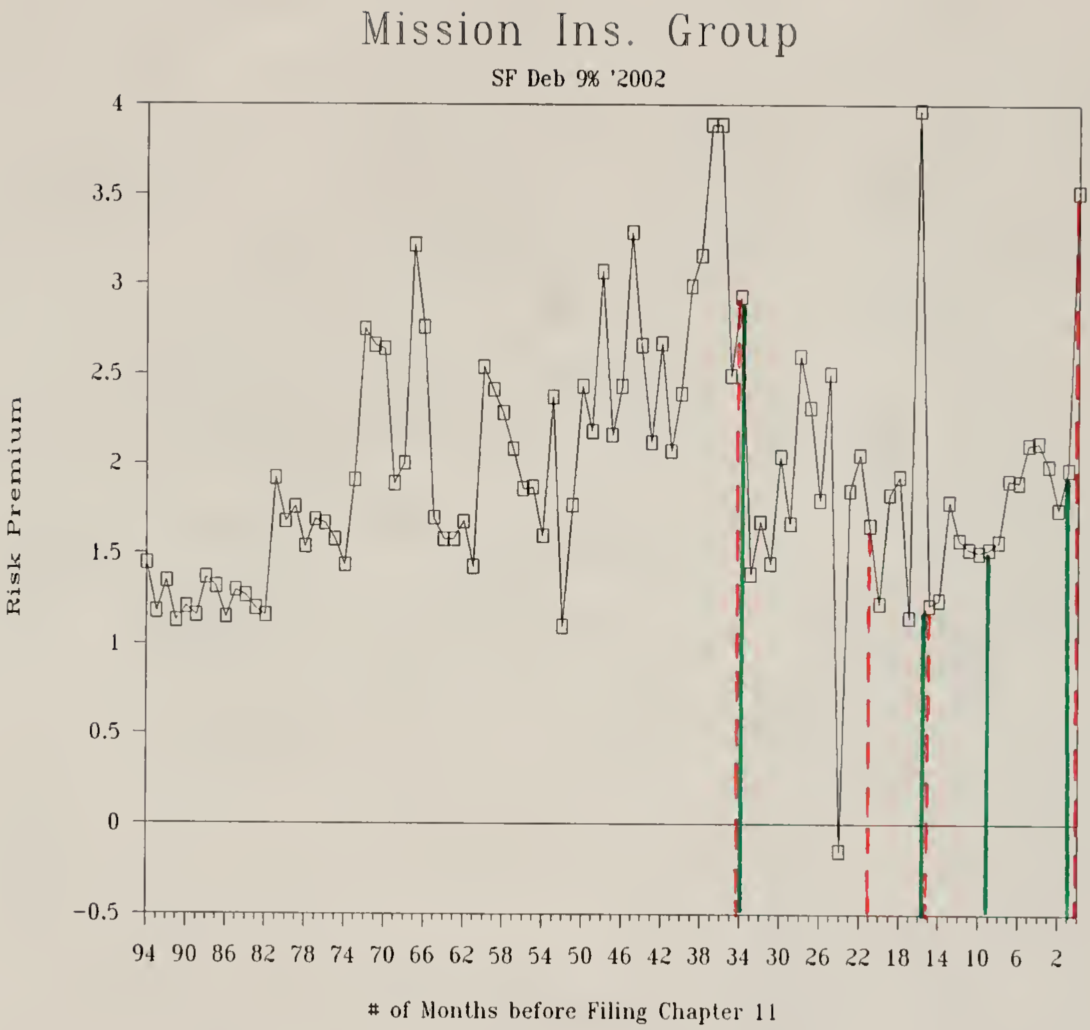

Mission Ins. Group
SF Deb 9% '2002
Risk Premium
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
94 90 86 82 78 74 70 66 62 58 54 50 46 42 38 34 30 26 22 18 14 10 6 2
# of Months before Filing Chapter 11

Figure A-32.

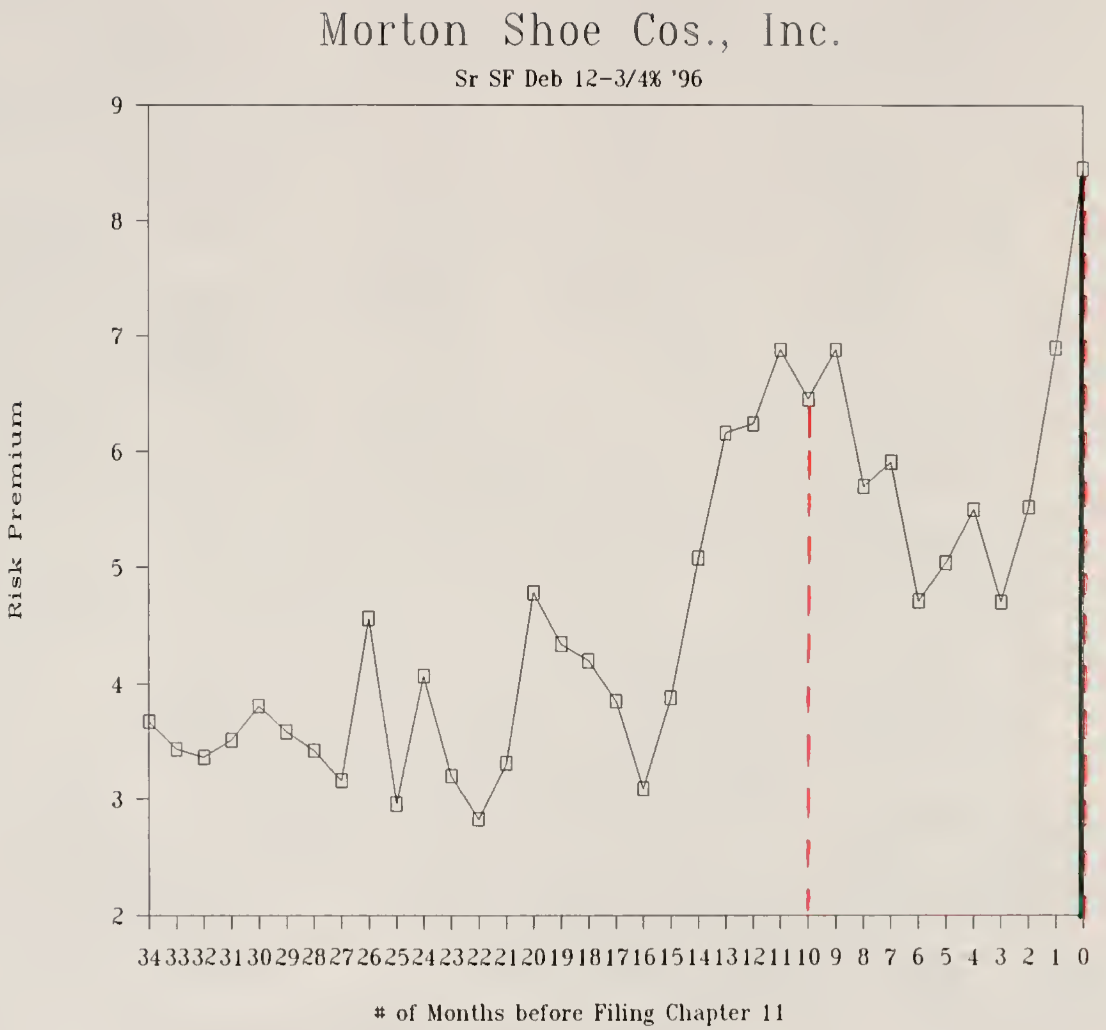
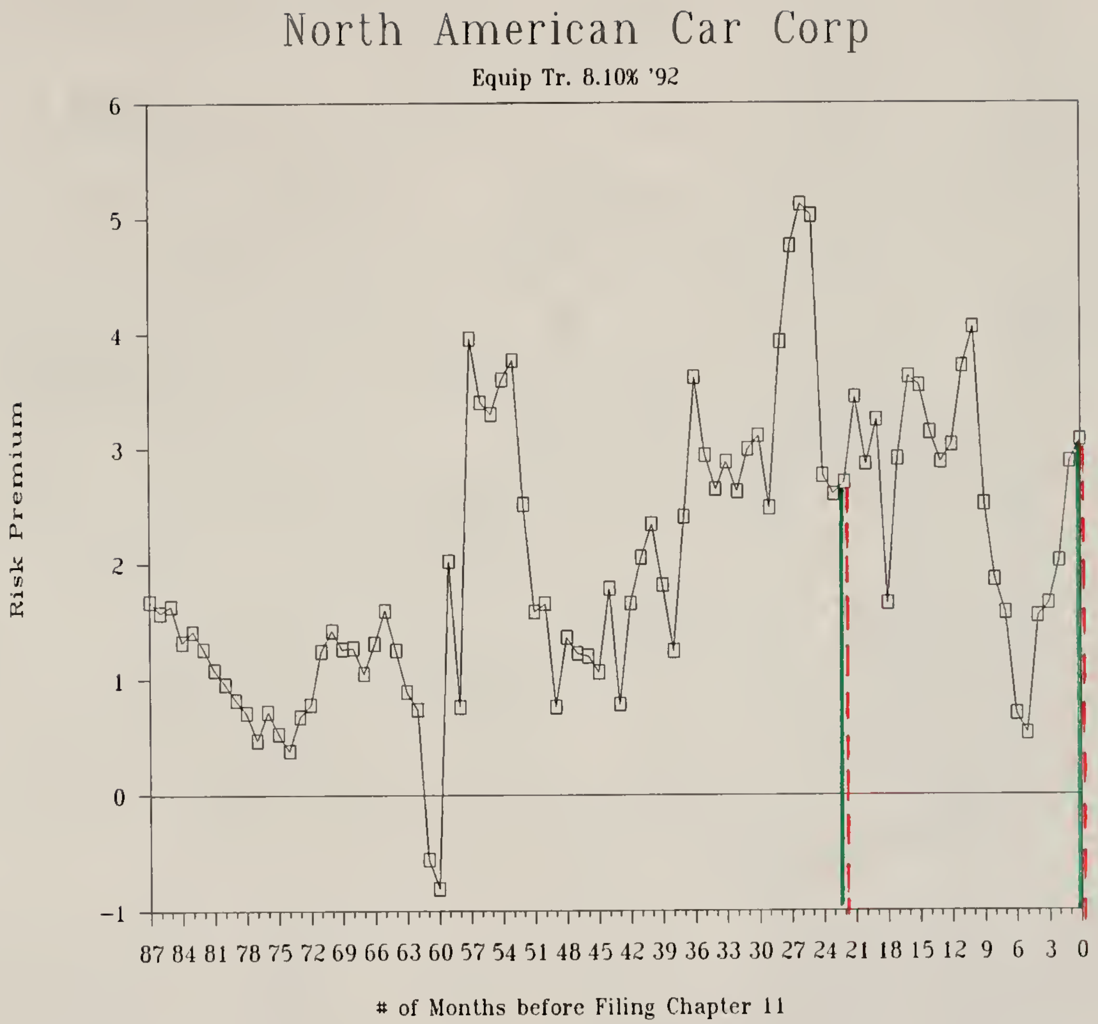

Morton Shoe Cos., Inc.
Sr SF Deb 12-3/4% '96
Risk Premium
9
8
7
6
5
4
3
2
34 33 32 31 30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-33.



North American Car Corp
Equip Tr. 8.10% '92
Risk Premium
6
5
4
3
2
1
0
-1
87 84 81 78 75 72 69 66 63 60 57 54 51 48 45 42 39 36 33 30 27 24 21 18 15 12 9 6 3 0
# of Months before Filing Chapter 11

Figure A-34.

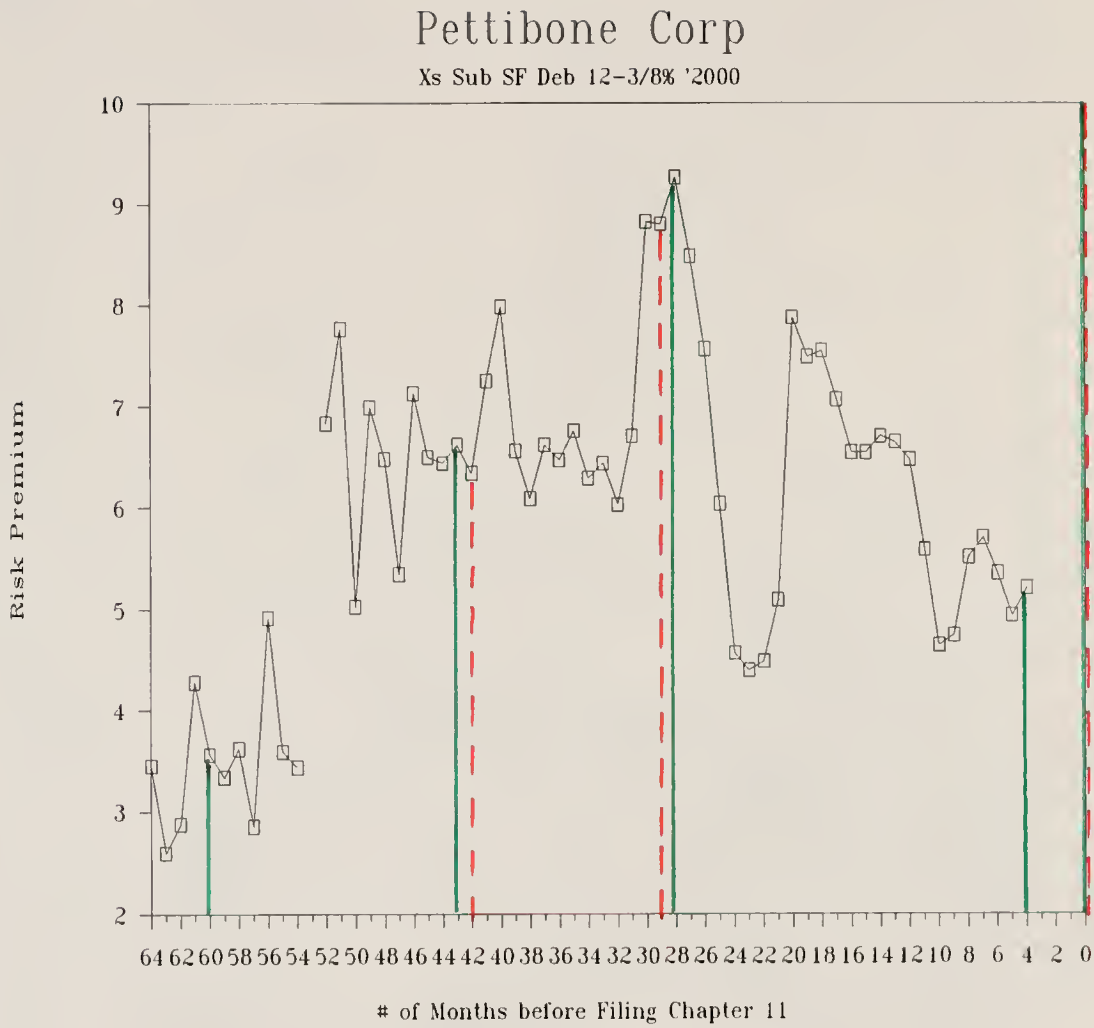
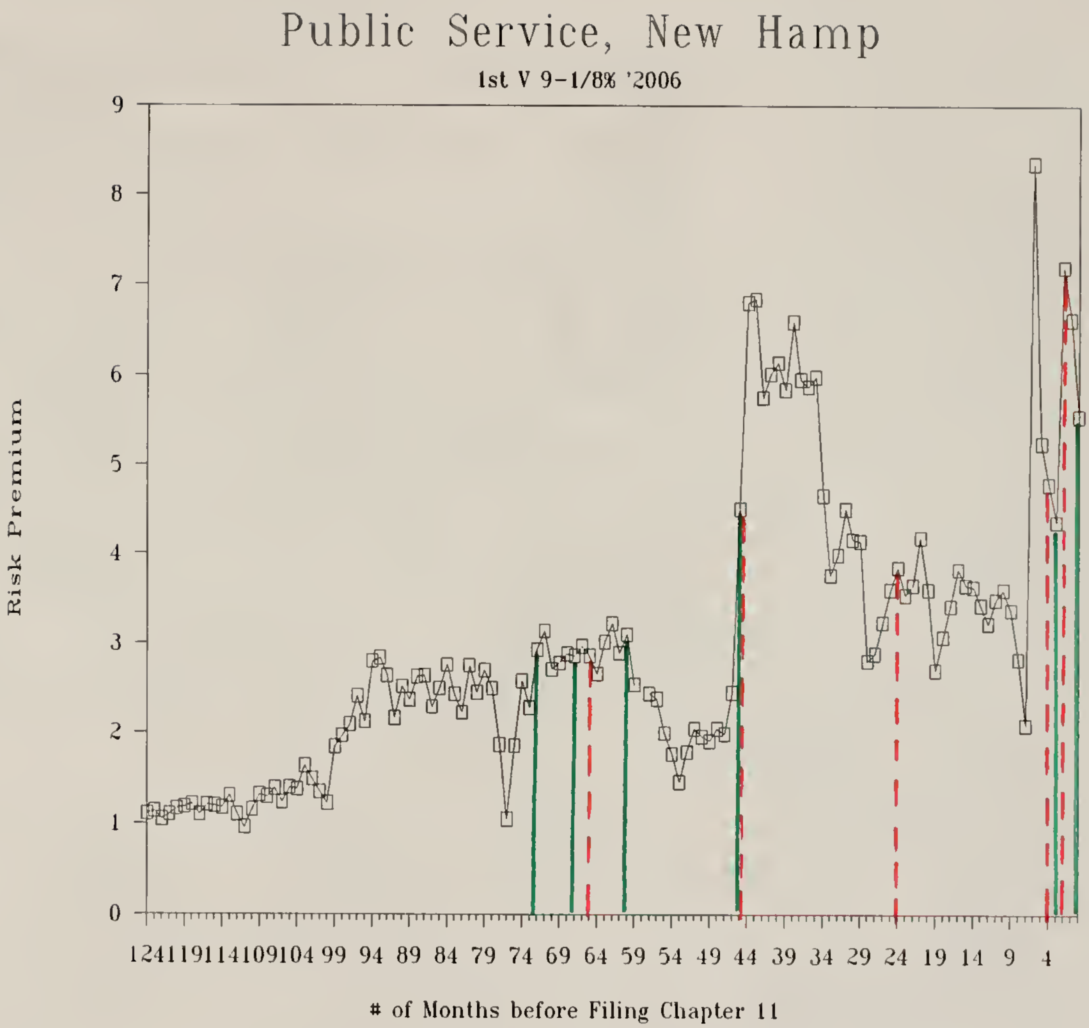
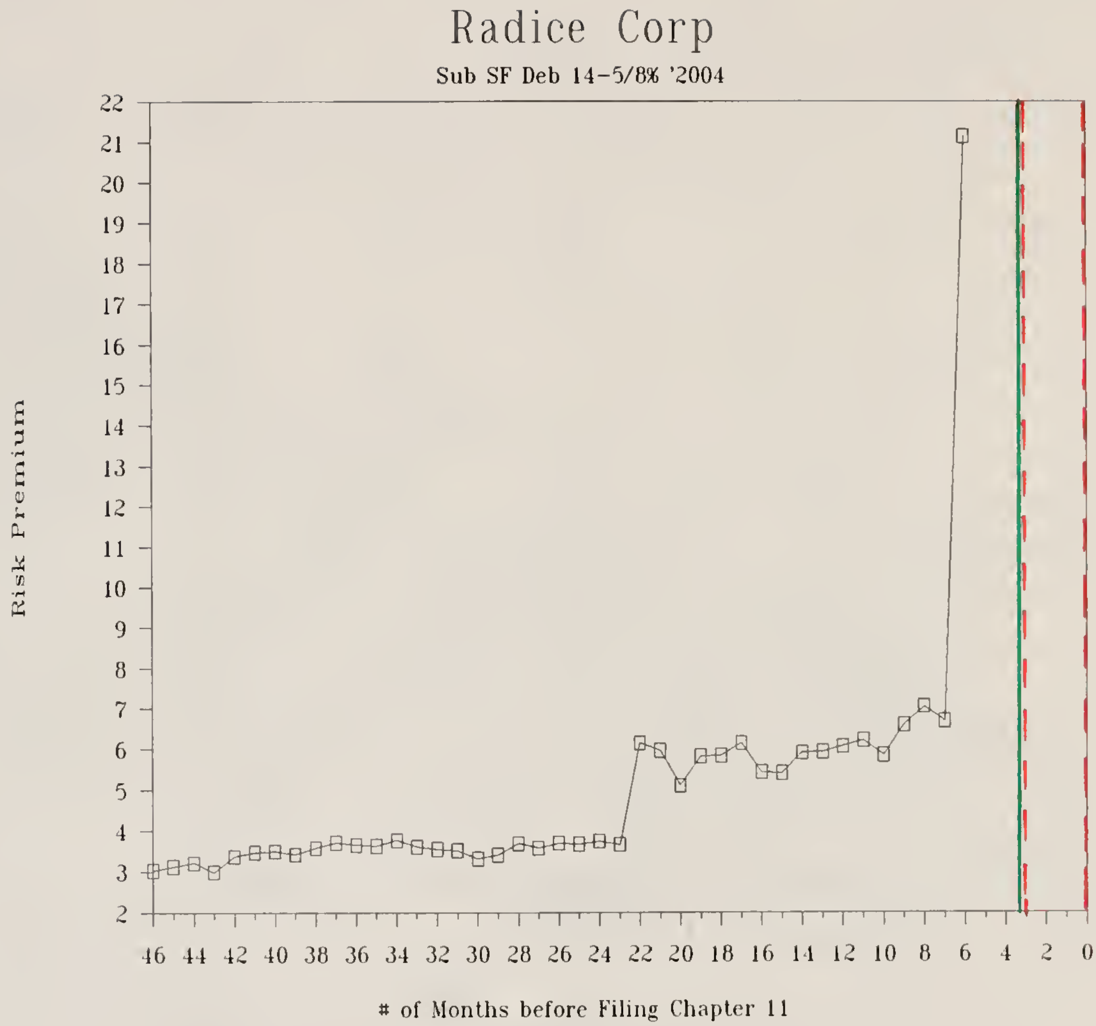

Pettibone Corp
Xs Sub SF Deb 12-3/8% '2000
Risk Premium
10
9
8
7
6
5
4
3
2
64 62 60 58 56 54 52 50 48 46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-35.



Public Service, New Hamp
1st V 9-1/8% '2006
Risk Premium
9
8
7
6
5
4
3
2
1
0
124119114109104 99 94 89 84 79 74 69 64 59 54 49 44 39 34 29 24 19 14 9 4
# of Months before Filing Chapter 11

Figure A-36.



Radice Corp
Sub SF Deb 14-5/8% '2004
Risk Premium
22
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-37.

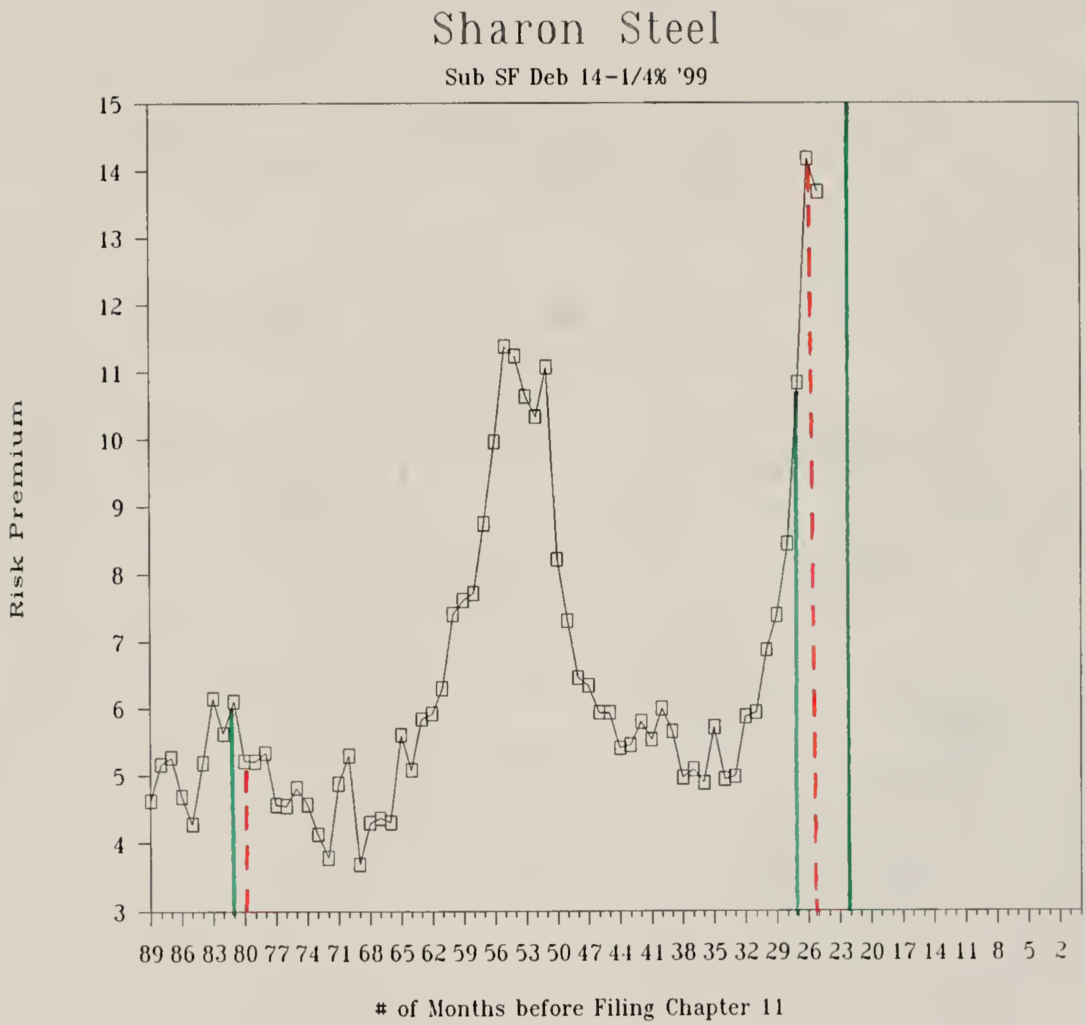

Sharon Steel
Sub SF Deb 14-1/4% '99
Risk Premium
15
14
13
12
11
10
9
8
7
6
5
4
3
89 86 83 80 77 74 71 68 65 62 59 56 53 50 47 44 41 38 35 32 29 26 23 20 17 14 11 8 5 2
# of Months before Filing Chapter 11

Figure A-38.

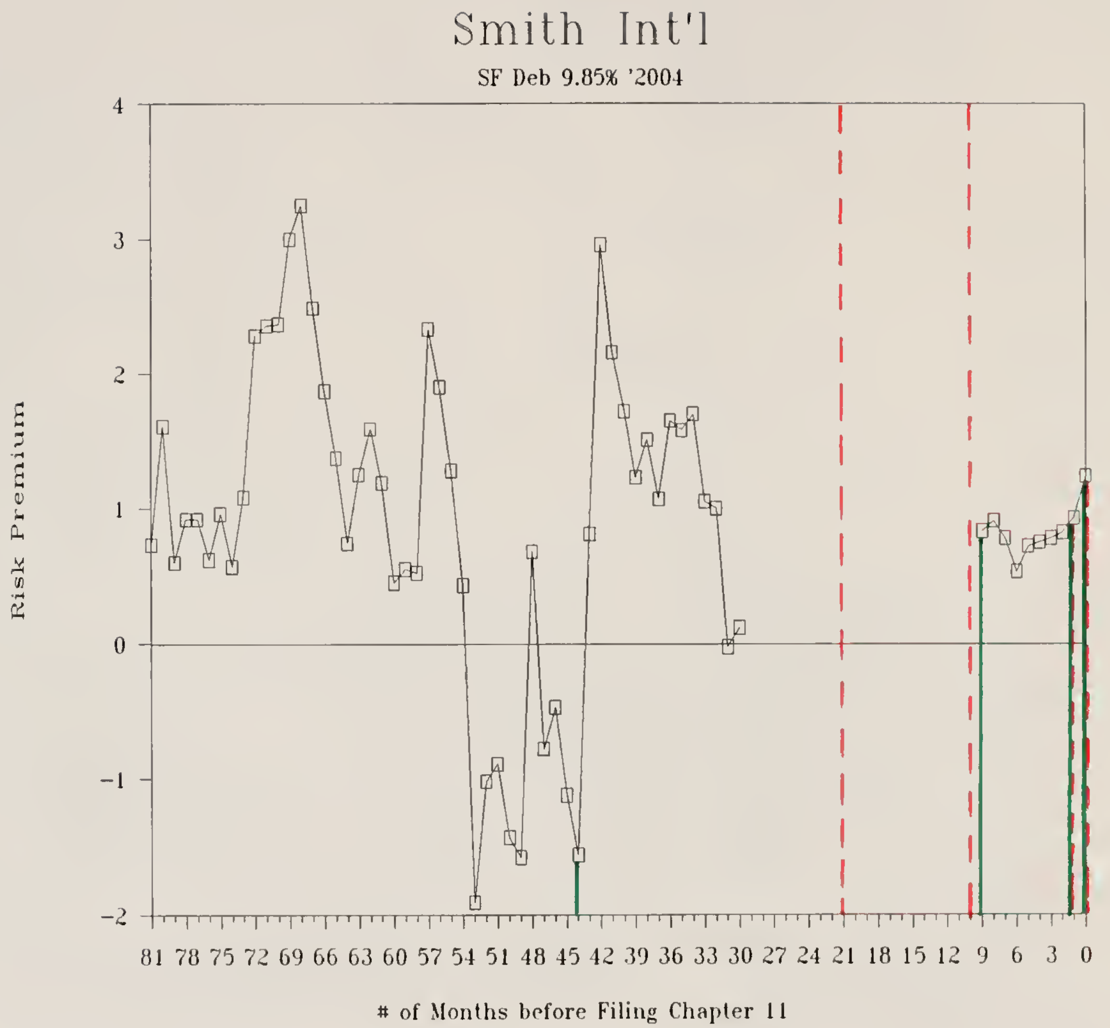
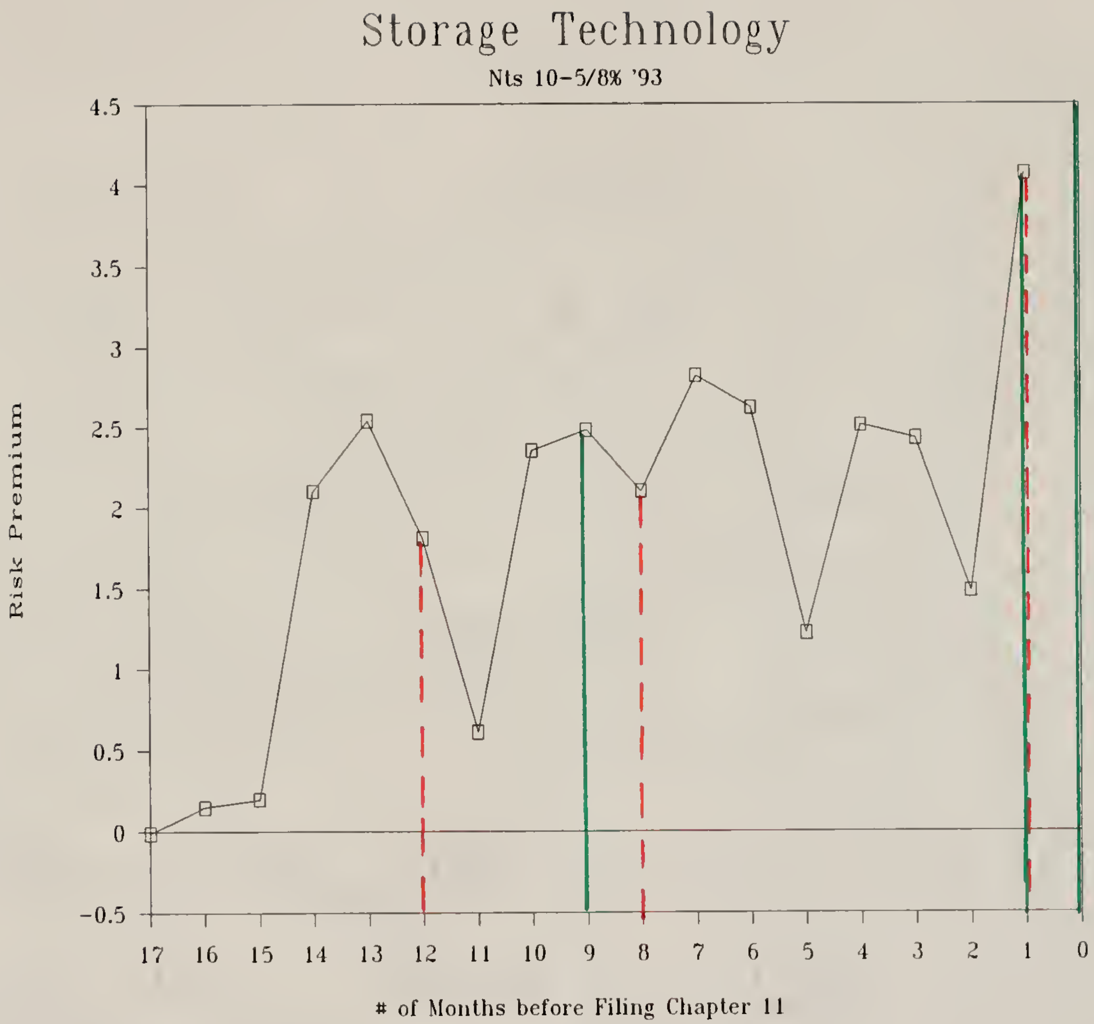

Smith Int'l
SF Deb 9.85% '2004
Risk Premium
4
3
2
1
0
-1
-2
81 78 75 72 69 66 63 60 57 54 51 48 45 42 39 36 33 30 27 24 21 18 15 12 9 6 3 0
# of Months before Filing Chapter 11

Figure A-39.



Storage Technology
Nts 10-5/8% '93
Risk Premium
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
-0.5
17
16
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
# of Months before Filing Chapter 11

Figure A-40.

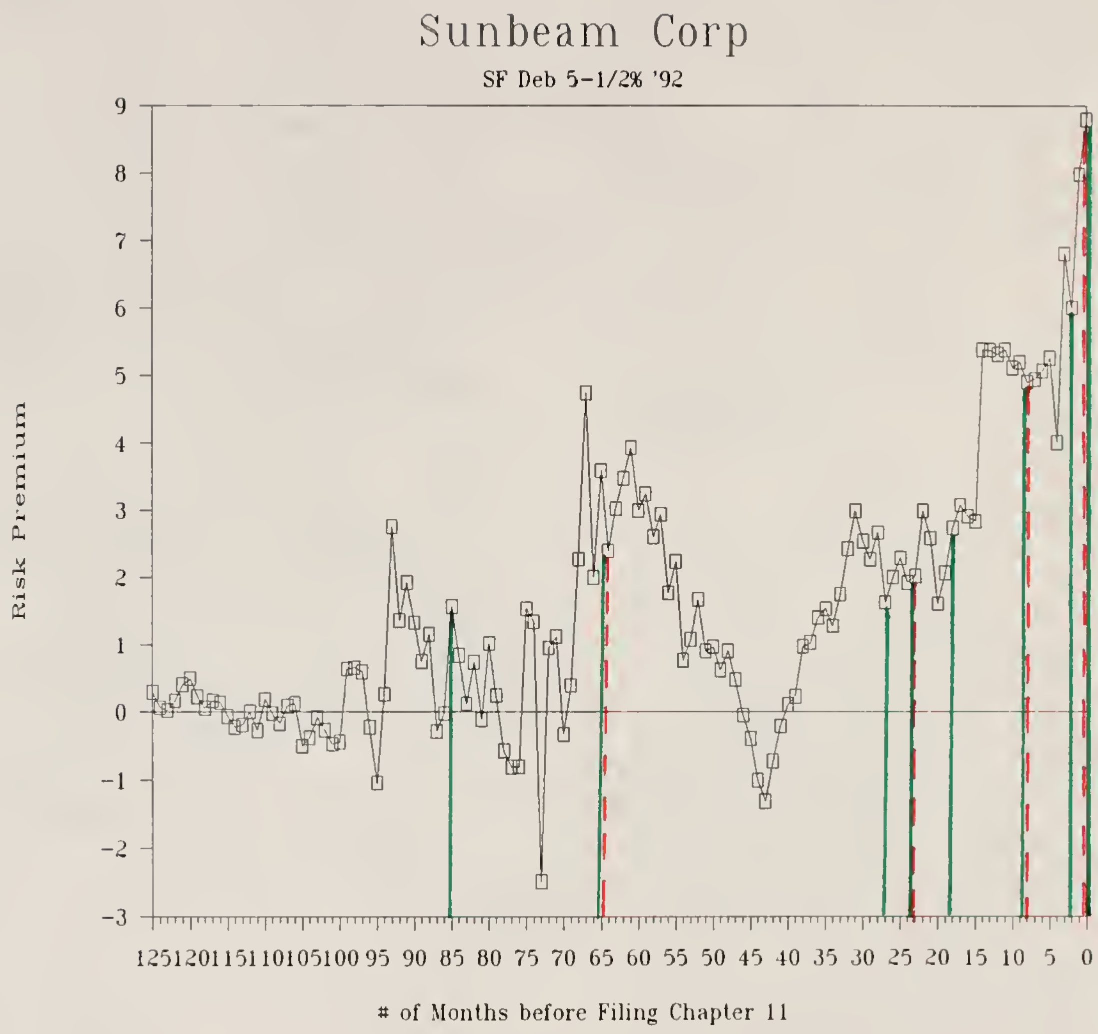

Sunbeam Corp
SF Deb 5-1/2% '92
Risk Premium
9
8
7
6
5
4
3
2
1
0
-1
-2
-3
125 120 115 110 105 100 95 90 85 80 75 70 65 60 55 50 45 40 35 30 25 20 15 10 5 0
# of Months before Filing Chapter 11

Figure A-41.

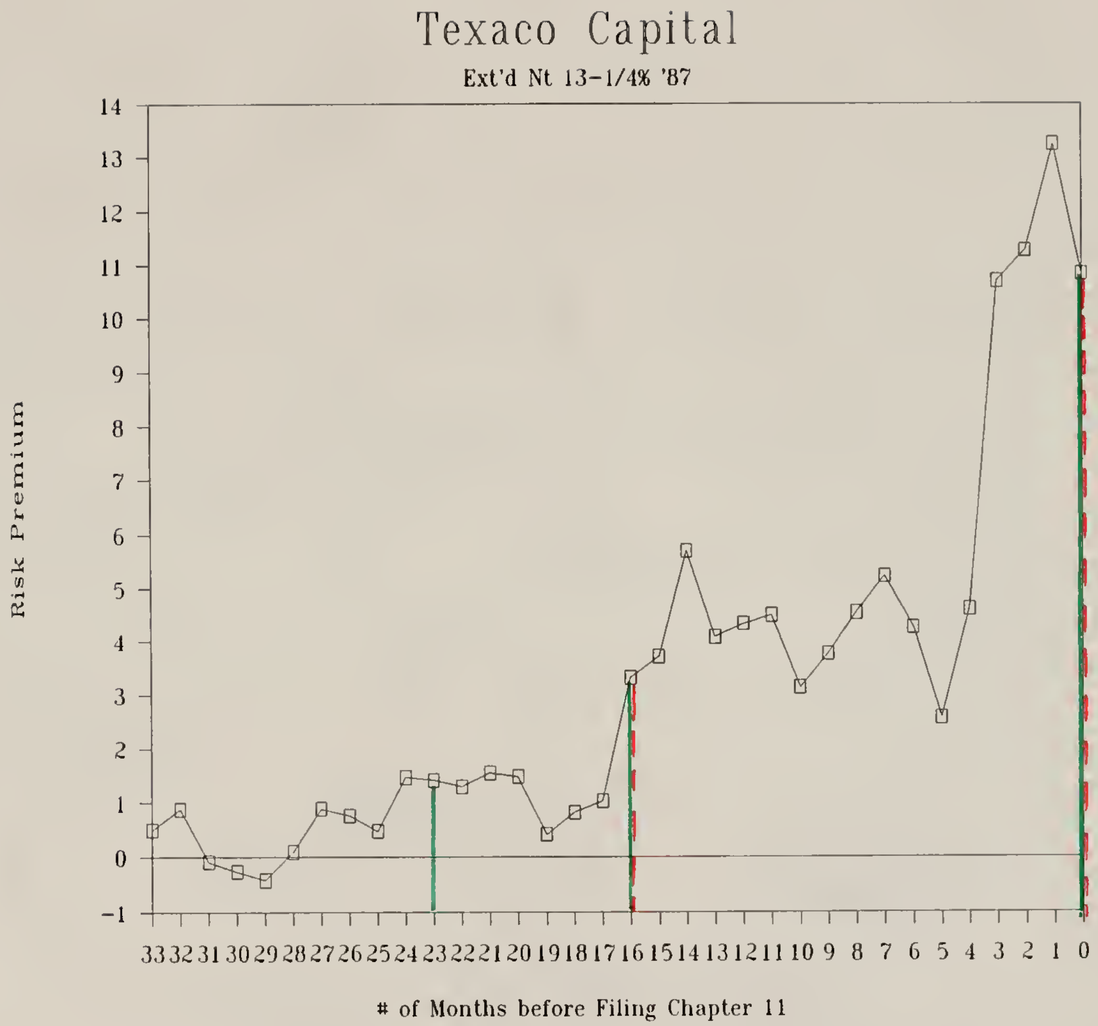

Texaco Capital
Ext'd Nt 13-1/4% '87
Risk Premium
14
13
12
11
10
9
8
7
6
5
4
3
2
1
0
-1
33 32 31 30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-42.

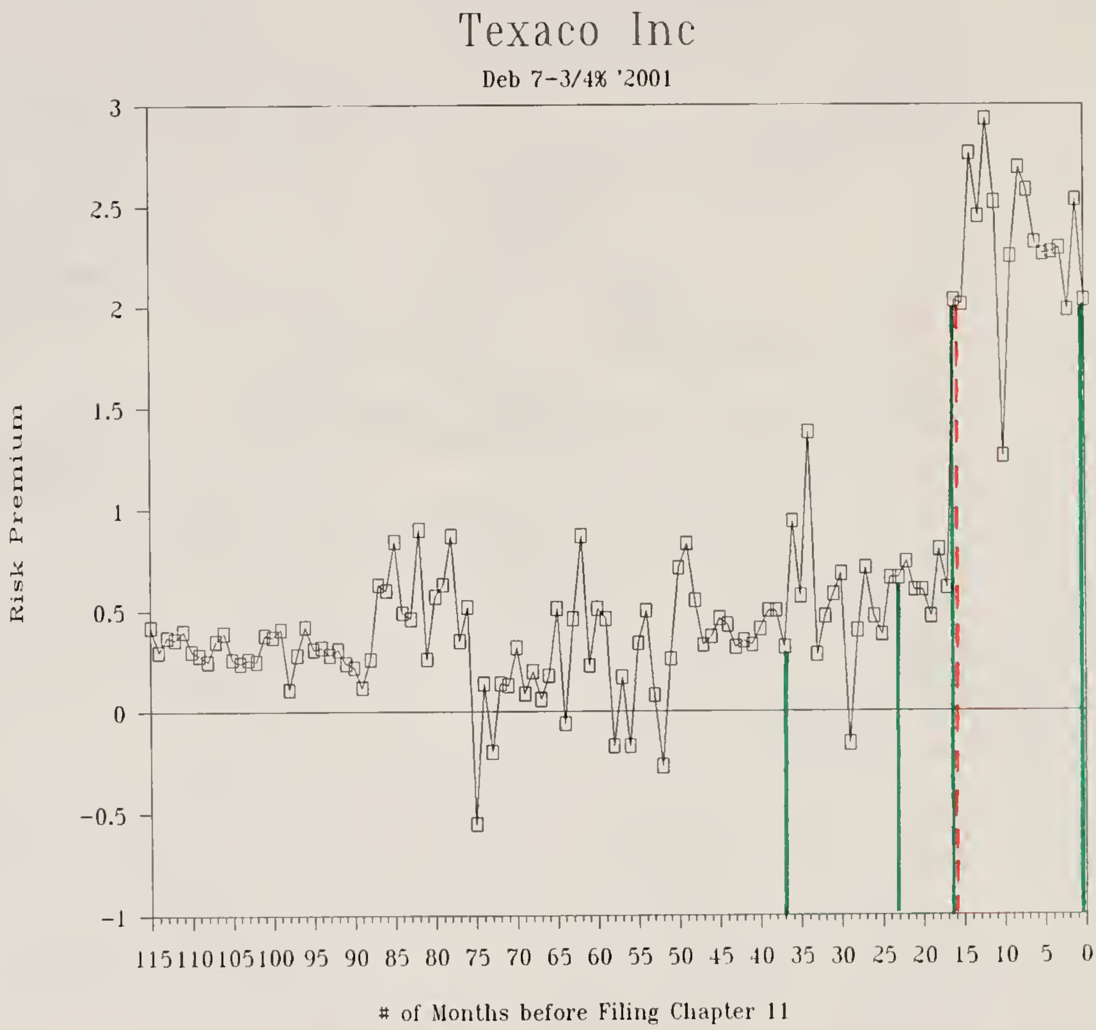
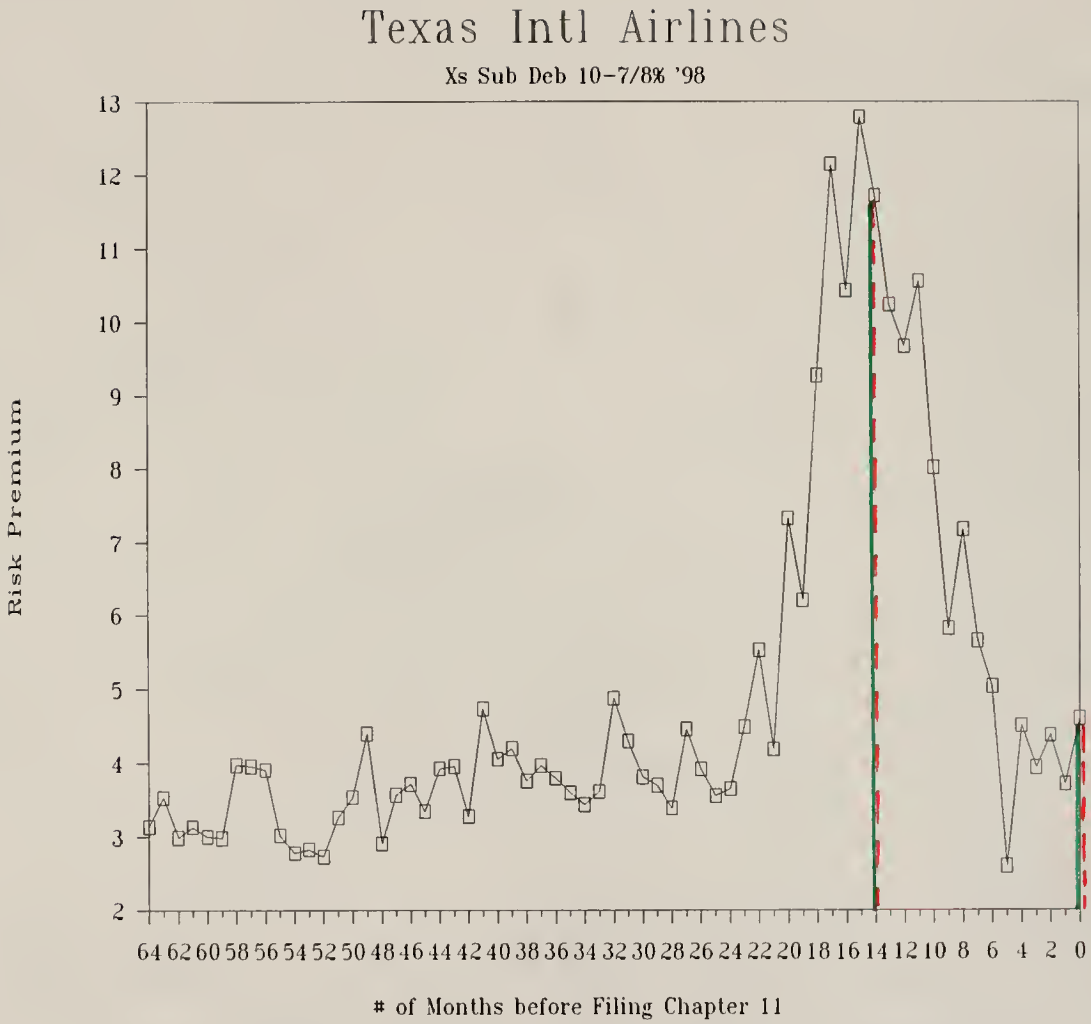

Texaco Inc
Deb 7-3/4% '2001
Risk Premium
3
2.5
2
1.5
1
0.5
0
-0.5
-1
115 110 105 100 95 90 85 80 75 70 65 60 55 50 45 40 35 30 25 20 15 10 5 0
# of Months before Filing Chapter 11

Figure A-43.



Texas Intl Airlines
Xs Sub Deb 10-7/8% '98
Risk Premium
13
12
11
10
9
8
7
6
5
4
3
2
64 62 60 58 56 54 52 50 48 46 44 42 40 38 36 34 32 30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0
# of Months before Filing Chapter 11

Figure A-44.

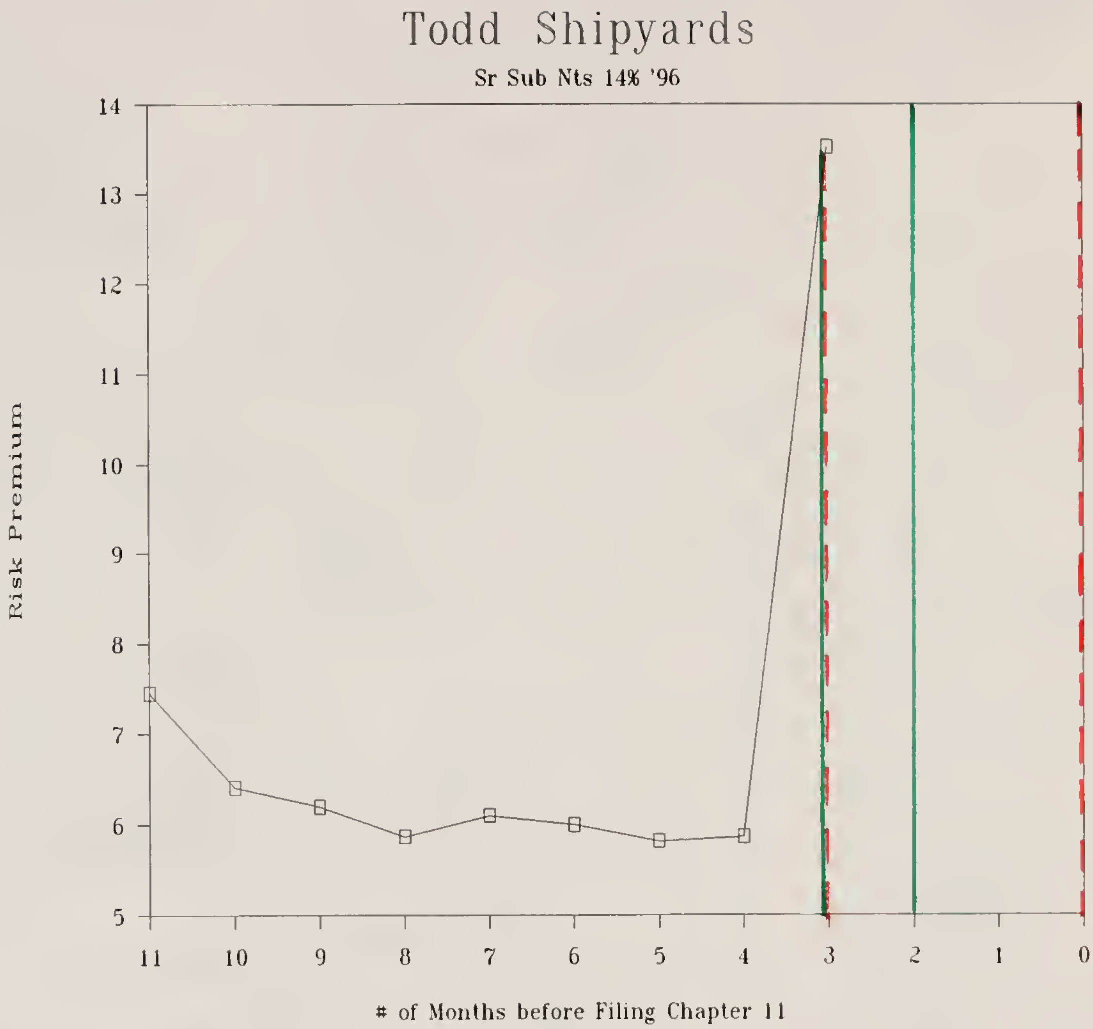
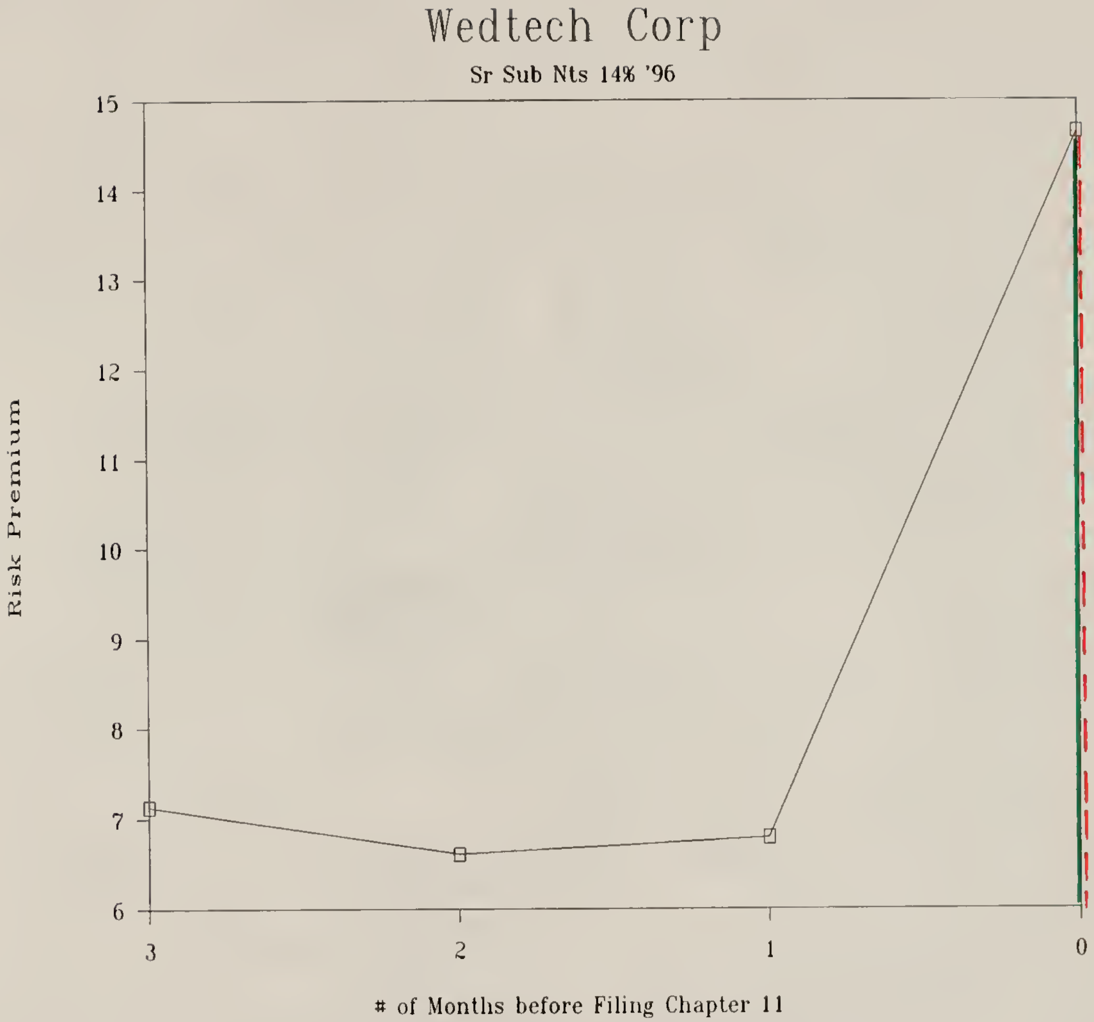
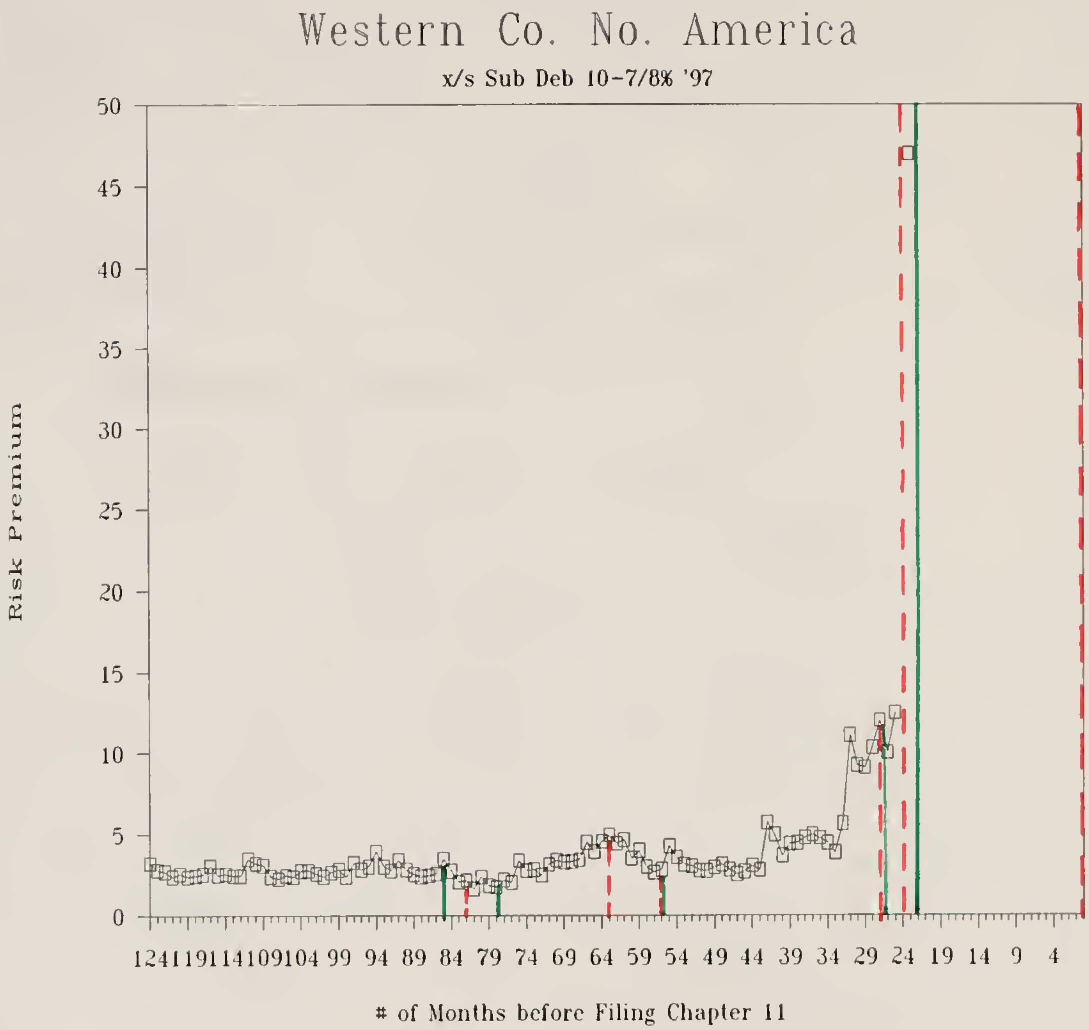

Todd Shipyards
Sr Sub Nts 14% '96
Risk Premium
14
13
12
11
10
9
8
7
6
5
11
10
9
8
7
6
5
4
3
2
1
0
# of Months before Filing Chapter 11

Figure A-45.



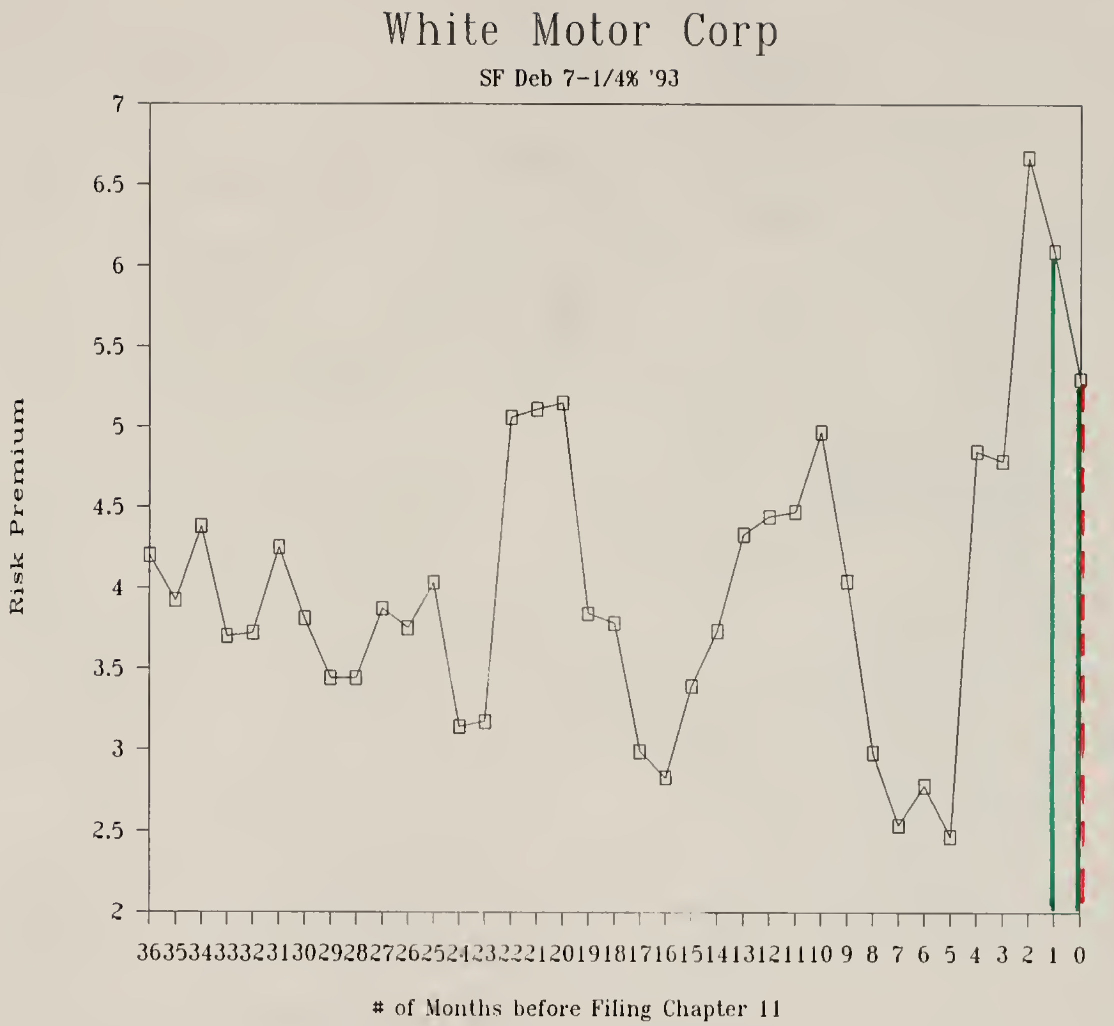
Wedtech Corp
Sr Sub Nts 14% '96
Risk Premium
15
14
13
12
11
10
9
8
7
6
3
2
1
0
# of Months before Filing Chapter 11

Figure A-46.



Western Co. No. America
x/s Sub Deb 10-7/8% '97
Risk Premium
50
45
40
35
30
25
20
15
10
5
0
124 119 114 109 104 99 94 89 84 79 74 69 64 59 54 49 44 39 34 29 24 19 14 9 4
# of Months before Filing Chapter 11

Figure A-47.



White Motor Corp
SF Deb 7-1/4% '93
Risk Premium
7
6.5
6
5.5
5
4.5
4
3.5
3
2.5
2
36 35 34 33 32 31 30 29 28 27 26 25 24 23 22 21 20 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2 1 0
# of Months before Filing Chapter 11

Figure A-48.

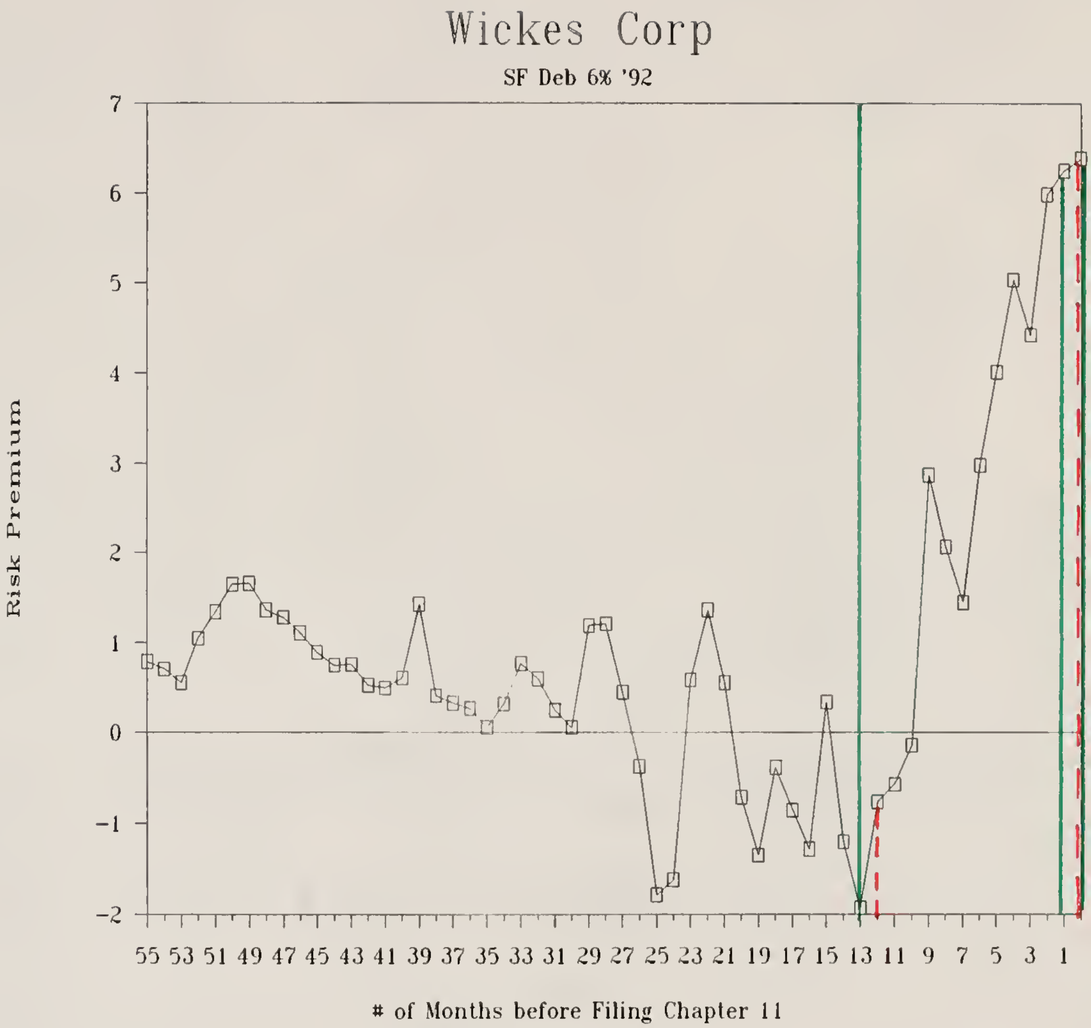
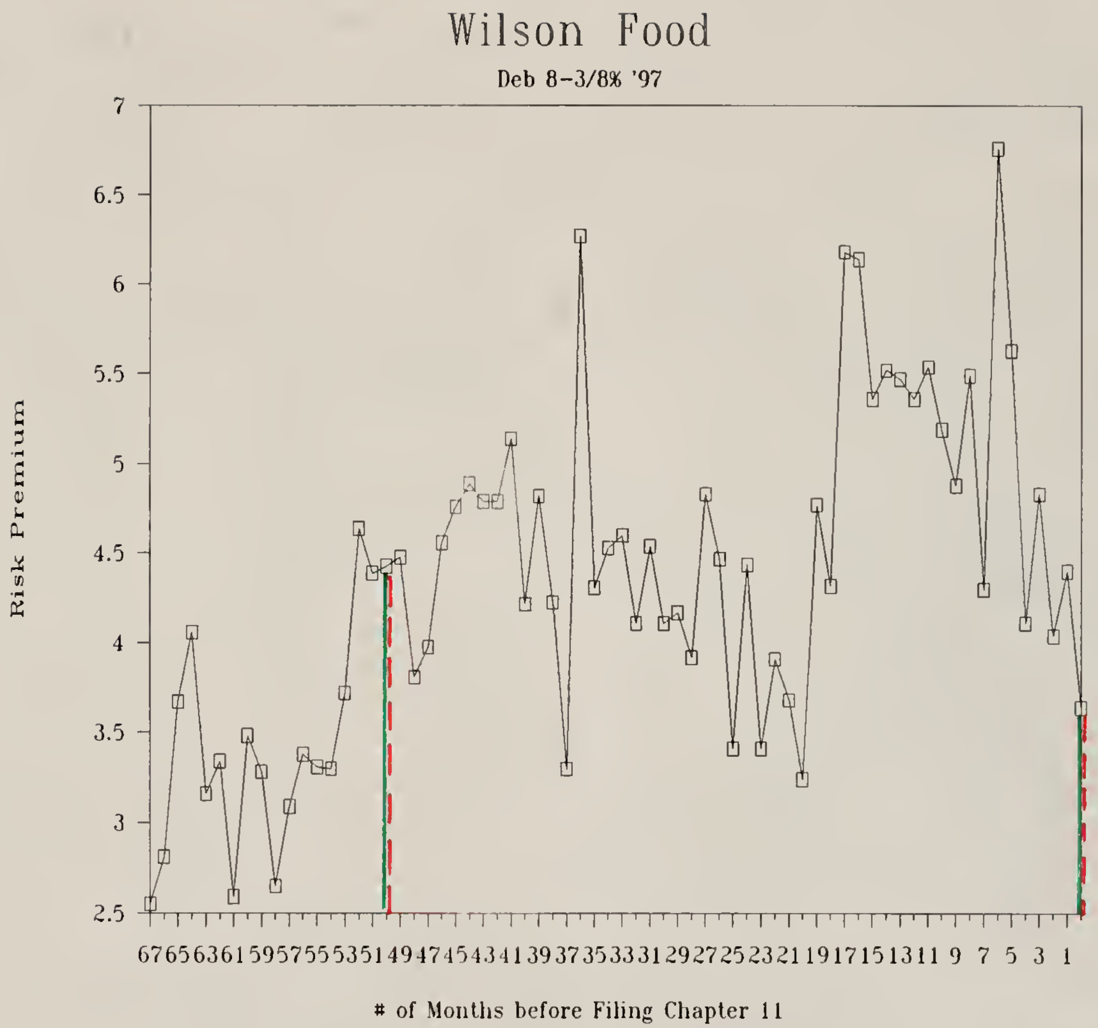

Wickes Corp
SF Deb 6% '92
Risk Premium
7
6
5
4
3
2
1
0
-1
-2
55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-49.



Wilson Food
Deb 8-3/8% '97
Risk Premium
7
6.5
6
5.5
5
4.5
4
3.5
3
2.5
67 65 63 61 59 57 55 53 51 49 47 45 43 41 39 37 35 33 31 29 27 25 23 21 19 17 15 13 11 9 7 5 3 1
# of Months before Filing Chapter 11

Figure A-50.

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BIOGRAPHICAL SKETCH

Mrs. Keqian Bi was born to Profs. Zhongjie Bi and Shaoxiang Huang on July 4, 1941 in Chungqing, China. She received a Bachelor of Science in Electrical Engineering degree from China University of Science and Technology in 1964. In 1982, she left China and came to the United States after a ten month stay in Switzerland, where she worked as a computer specialist. In 1984, she entered the graduate program in Finance at the University of Florida. She had received her M.A. in Finance in August 1986, and will receive her Ph.D. in Finance in August 1989.

Starting August 1989, she will begin working as an Associate Professor of Finance at the McLaren College of Business at the University of San Francisco.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Roy L. Crum, Chairman
Professor of Finance, Insurance, and Real Estate

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

H. Levy

Haim Levy, Cochairman
Walter J. Matherly Professor of Finance

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

David A. Denslow
Professor of Economics

This dissertation was submitted to the Graduate Faculty of the Department of Finance, Insurance, and Real Estate in the College of Business Administration and to the Graduate School and was accepted as partial fulfillment of the requirements for the degree of Doctor of Philosophy.

August 1989

Dean, Graduate School

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